Adaptive trading system for sustainable forex markets

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ABSTRACT

This study presents a sustainable and ethically aligned algorithmic trading system for the Euro/United States Dollar (EURUSD) currency pair, integrating reinforcement learning (RL) with a Sugeno-type fuzzy inference mechanism. The framework emphasizes responsible AI principles by combining adaptability and interpretability to support transparent and explainable financial decision-making. Historical EURUSD M15 data from 2020 to 2023 were used for training, while 2024 data served for out-of-sample testing. The system employs EMA50-based state classification, tabular state–action–reward–state–action or SARSA learning, and a fuzzy logic layer comprising 27 expert-defined rules. During backtesting, the agent executed 785 trades, achieving a net profit of USD 61.85, a profit factor of 1.04, and a balanced win–loss ratio. Risk-adjusted analysis showed moderate resilience (sharpe ratio = 0.53) and a maximum drawdown of 59.74%. The model demonstrated strong equity stability (ESI = 0.9672) and sensitivity to macroeconomic events identified through cumulative sum (CUSUM) analysis. While the system maintained capital preservation and interpretability, responsiveness under volatile conditions requires improvement. Future work will focus on adaptive exit logic, volatility-aware reward mechanisms, and regime-sensitive policy optimization. This study contributes to advancing sustainable, transparent, and risk-aware artificial intelligence (AI) frameworks in algorithmic trading.

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1. INTRODUCTION

The application of artificial intelligence (AI) has transformed algorithmic trading, particularly in the highly volatile foreign exchange (FOREX) market. Traditional rule-based strategies often fail to adapt to rapid intraday fluctuations, while reinforcement learning (RL) enables agents to refine their strategies through interaction with market data. Among RL methods, the state–action–reward–state–action (SARSA) algorithm offers adaptability. However, its limited interpretability reduces its suitability in regulated and risk-sensitive environments [1]–[4]. Fuzzy inference systems (FIS) provide a transparent, rule-based framework that enhances interpretability and auditability, making them valuable for responsible AI applications in finance. The SARSA-FIS hybrid model combines RL adaptability with fuzzy logic transparency, addressing increasing demands for oversight, transparency, and ethical decision-making in automated financial systems [2], [5], [6].

Recent studies demonstrate the effectiveness of hybrid intelligent models that merge data-driven learning with structured rule systems. Hybrid architectures such as long short-term memory–convolutional neural networks (LSTM-CNNs), signal decomposition models (variational mode decomposition or VMD and singular spectrum analysis or SSA), and recurrent networks (bidirectional long short-term memory (BiLSTM) and gated recurrent unit (GRU)) have achieved improved forecasting accuracy for complex time series [6]–[8]. Additionally, optimization techniques such as genetic algorithms and stochastic gradient methods have enhanced model robustness and training efficiency in high-frequency environments [9]–[11].

Despite these advancements, few approaches incorporate sustainability-aware mechanisms such as drawdown limits, volatility filtering, or capital preservation. With the growing focus on environmental, social, and governance (ESG) principles and the United Nations Sustainable Development Goals (SDGs), ethical and sustainable design in trading algorithms has become increasingly important [2], [12], [13]. Structural approaches such as triangular arbitrage and directional change techniques have also shown value in managing volatility and aligning trading behavior with market regimes [14]–[16]. As AI becomes more embedded in financial infrastructure, the demand for explainable, ethical, and override-capable trading systems continues to grow [17]–[19]. Adaptive frameworks that integrate behavioral sensitivity, capital control, and predictive resilience are increasingly favored, particularly in the retail forex domain [20], [21].

Traditional baselines in algorithmic trading such as moving average crossovers, buy-and-hold strategies, and standalone fuzzy systems often fail to maintain performance consistency under dynamic volatility conditions. While these methods provide interpretability or stability in specific regimes, they lack adaptive learning and contextual awareness. RL approaches, such as Q-learning, improve adaptability but remain limited in transparency and risk control. The SARSA-FIS hybrid model extends beyond these baselines by combining real-time policy updates with rule-based interpretability, enabling a more sustainable and responsible approach to AI-driven financial systems.

This study proposes a sustainable and interpretable algorithmic trading agent for the Euro/United States Dollar (EURUSD) currency pair, built using a hybrid SARSA-FIS framework. The objective is to integrate RL with fuzzy logic to create a system that is both adaptive to dynamic market conditions and transparent in its decision-making fulfilling key principles of responsible AI in finance. The agent design integrates exponential moving average (EMA)-based state classification, volatility-sensitive reward shaping, and drawdown-aware execution policies to balance adaptability with ethical risk control.

The SARSA-FIS agent was trained on EURUSD M15 data from 2020 to 2023 and backtested on 2024 out-of-sample data. A total of 785 trades were executed, yielding a net profit of USD 61.85 (initial capital USD 100) with a profit factor of 1.04 and a balanced win–loss ratio. Risk-adjusted results showed moderate returns (sharpe ratio = 0.53), strong equity stability (ESI = 0.9672), and sensitivity to macroeconomic shifts detected through cumulative sum (CUSUM) analysis. These findings demonstrate the model's structural robustness and interpretability while identifying opportunities for enhancing regime adaptation and exit logic. In summary, the proposed SARSA-FIS framework bridges the gap between adaptability and explainability in AI-driven financial systems, aligning algorithmic performance with responsible AI and sustainability principles. Overall, this research advances the development of ethical, transparent, and resilient trading systems for the modern financial environment.

2. METHOD

The trading agent was developed using a SARSA–FIS hybrid framework, combining RL adaptability with fuzzy logic transparency. The SARSA algorithm was selected for its capability to iteratively update action–value estimates based on market feedback, while the Sugeno-type FIS ensured interpretability and auditability of decisions. The integration of these two approaches supports both adaptive learning and responsible AI design, meeting the needs of risk-sensitive financial systems [1], [4], [16], [22]. A hybrid SARSA-FIS structure thus combines learning flexibility with rule-based explainability, satisfying both adaptation and auditability requirements [2], [15].

2.1. Development environment

The development was implemented across three platforms: Python 3.10 for SARSA RL simulation, MATLAB R2023a for FIS modeling, and MetaTrader 5 (build 4755) for real-time implementation and backtesting. The overall workflow is illustrated in Figure 1. Historical EURUSD 15-minute candlestick data (January 2020–December 2024) were retrieved from MetaTrader 5. Data from 2020–2023 were used for model training, and 2024 data served as out-of-sample testing, consistent with standard time-series validation practices [5]. This multi-platform workflow ensures the reproducibility of the experimental process across simulation, modeling, and deployment stages.

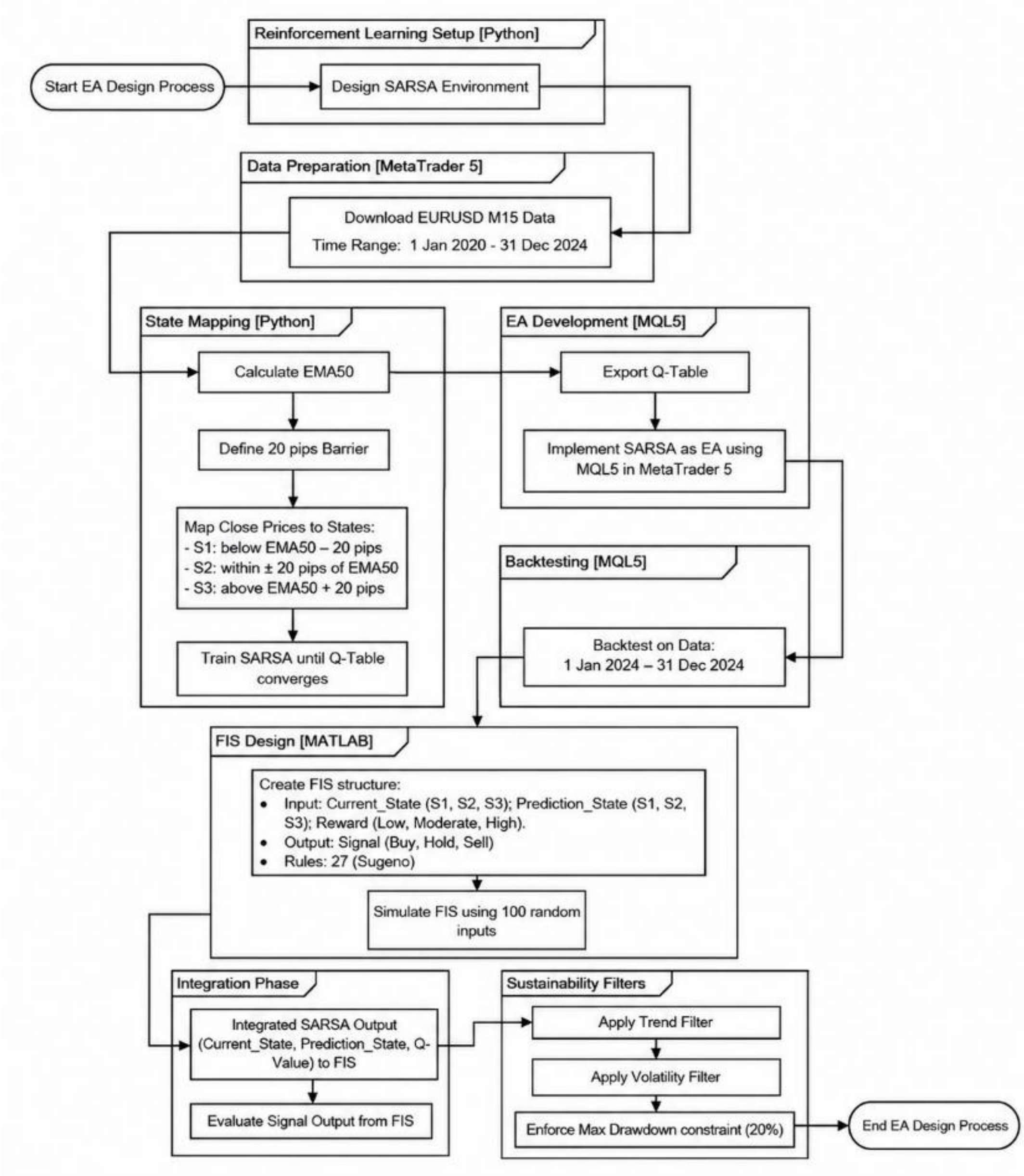

Figure 1. SARSA-FIS trading agent development flowchart illustrating the sequential process of RL setup, fuzzy inference modeling, system integration, and sustainable backtesting

2.2. SARSA RL framework

The SARSA environment was modeled using tabular RL. States were discretized into three classes (S1, S2, and S3) which are based on EMA50 deviations using ±20 pip thresholds. Actions were (sell, hold, and buy), resulting in a 3×3 Q-table. Learning parameters were set as: learning rate (α)=0.1, discount factor (γ)=0.9, initial ε=0.3 with adaptive decay ($\varepsilon \leftarrow 0.999 \times \varepsilon$ per step, down to 0.05). Training ran for 500 episodes or until convergence, using the SARSA update rule shown in (1). The learned Q table was exported to an expert advisor (EA) in MetaTrader 5.

$$Q(s_{t,}a_t) \leftarrow Q(s_{t,}a_t) + \alpha\left[r_{t+1} + \gamma Q(s_{t+1,}a_{t+1}) - Q(s_{t,}a_t)\right] \quad (1)$$

Here, $Q(s_t, a_t)$ represents the expected value of taking action a_t in state s_t, while r_{t+1} denotes the reward received after transitioning to state s_{t+1} and selecting action a_{t+1}. The algorithm updates its policy iteratively by incorporating both the immediate reward and the expected future return, balancing exploration and exploitation in the learning process. Python modules NumPy and Pandas were used for simulation, environment transition, and Q-table updates. At convergence, the Q-table was embedded into a custom expert advisor or EA written in MQL5 for real-time execution. These implementation details facilitate full reproducibility of the learning and deployment process. The EA parameters included a fixed lot size of 0.01, a 20-pip spread limit, and a 15-minute cooldown between trades. Risk control logic capped drawdown at 20% via dynamic equity tracking.

2.3. FIS design

For interpretability, a Sugeno-type FIS was developed using MATLAB. It accepted three inputs: current state, predicted next state, and reward; and produced one output signal. Each input was modeled using three fuzzy membership functions (low, moderate, high). The output was encoded as: sell = 0.5, hold = 1.5, and buy = 2.5. A total of 27 fuzzy rules covered all combinations of inputs.

As shown in Figure 2, the FIS operates as a modular decision-enhancing layer within the broader SARSA-FIS architecture. Upon receiving normalized Q-values and rewards from the SARSA agent, the inputs are passed to a fuzzy rule base that evaluates them using the prod method for logical conjunctions and probor for disjunctions. The FIS layer evaluated Q-values and rewards using prod and probor methods for fuzzy logic reasoning. A Sugeno engine with sum aggregation and wtaver defuzzification was used to generate crisp trading signals in real time, enhancing decision transparency and interpretability within the hybrid model. To ensure rule coverage, the FIS was tested using 100 randomized input vectors [22]. Integration was achieved by mapping Q-values to fuzzy classes: low ($Q < 4.35$), moderate ($4.35 \leq Q < 10.02$), and high ($Q \geq 10.02$). Combined with state variables, these inputs were fed into the FIS to generate the trading signal.

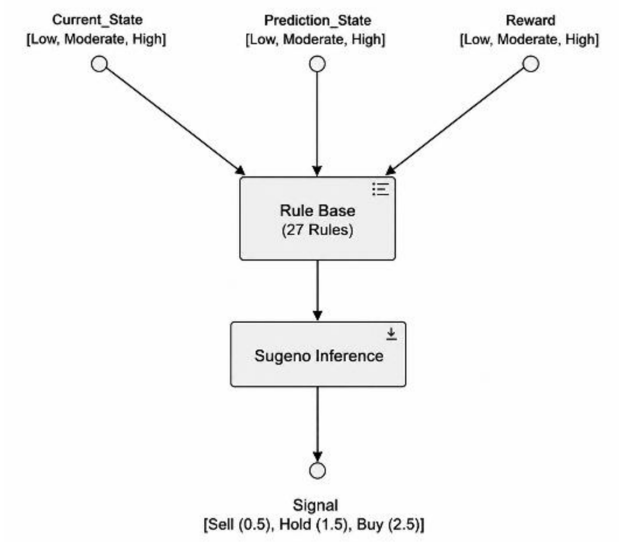

Figure 2. Block diagram of the Sugeno-type FIS used in the SARSA-FIS trading agent, showing input variables, rule base, and signal output structure

2.4. Reward and sustainability mechanisms

A directional reward structure was implemented within the SARSA environment to guide learning, as illustrated in Figure 3. The reward map was designed to favor upward transitions (e.g., S1 → S2, S2 → S3) and penalize downward or lateral moves, accelerating convergence while aligning with trend-following strategies. Training used a Bellman-based epsilon-greedy policy and terminated after 1,000 episodes or Q-value stabilization.

Three sustainability filters were implemented. A trend filter used EMA50 and EMA10 alignment to validate trades. A volatility filter used a 14-period average true range (ATR), blocking trades when ATR exceeded twice its median. A drawdown limiter deactivated the agent after a 20% equity drop. These filters promoted responsible risk-taking [15], [22]. Final model files were saved via MetaTrader 5 I/O system. The Q-table was saved as “SARSA_QTable_EURUSD.txt,” the fuzzy weights as “SARFIS_Weights_EURUSD.txt,” and drawdown data as “MaxDrawdownStatus.txt.” This ensured cross-session continuity, model reproducibility, and facilitated post-hoc auditability.

Figure 3. SARSA training environment illustrating state transitions (S1–S3), possible actions (stay, next, jump), and corresponding reward assignments

2.5. System architecture

A structured sequence diagram as in Figure 4 was developed to illustrate the SARSA-FIS EA workflow, encompassing data acquisition, state classification, action selection, FIS evaluation, and execution filtering (MACD, EMA10, triangular hedging). Each module interacts transparently with others, reinforcing interpretability and reproducibility across the full trading pipeline [4], [14].

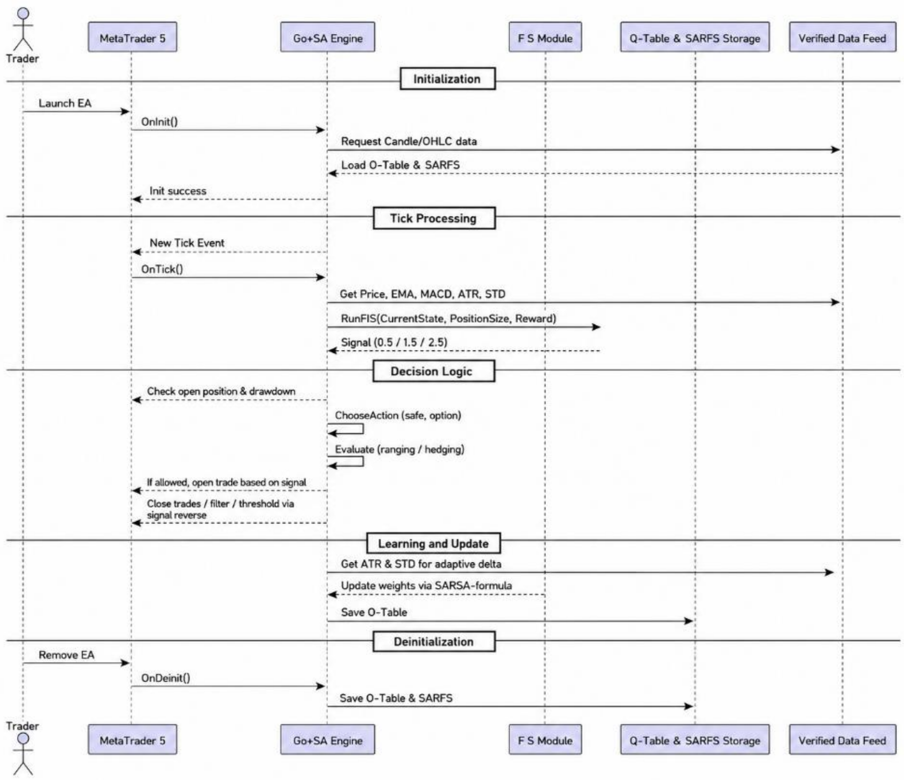

Figure 4. Sequence diagram of the SARSA-FIS EA architecture illustrating initialization, decision logic, learning updates, and sustainable trading workflow in MetaTrader 5

3. RESULTS AND DISCUSSION

The SARSA-FIS trading agent was evaluated using one year of out-of-sample EURUSD M15 data. The system achieved marginal profitability, with a profit factor slightly above unity, indicating near break-even performance under realistic market conditions.

3.1. Trading performance metrics

Table 1 presents the backtest summary. The results indicate a balanced distribution between winning and losing trades, suggesting stable decision behavior rather than overfitting. The expected payoff remains positive but low, reflecting a conservative trading profile. However, the relatively high drawdown highlights vulnerability during prolonged adverse conditions, indicating that while trade-level risk is controlled, cumulative risk remains a key limitation.

Growth metrics such as arithmetic holding period return (AHPR) (0.14%) and geometric holding period return (GHPR) (0.06%) reflect a conservative and low-yield strategy. Correlation between profit and excursion measures (maximum favorable excursion (MFE) = 0.77, MAE = 0.79) suggests volatility-sensitive outcomes. These findings suggest that the SARSA-FIS framework achieves micro-level consistency in trade execution but remains limited in macro-level robustness under sustained volatility.

Table 1. Performance summary of the SARSA-FIS trading agent based on one-year backtesting results for EURUSD (M15 Timeframe)

Metric	Value
Total trades	785
Profit trades (%)	397 (50.57%)
Loss trades (%)	388 (49.43%)
Gross profit (USD)	1638.23
Gross loss (USD)	-1576.38
Net profit (USD)	61.85
Profit Factor	1.04
Expected payoff (USD)	0.08
Sharpe ratio	0.53
Recovery factor	0.64
Max drawdown (USD)	96.66
Max drawdown (%)	59.74%
Average profit trade (USD)	4.13
Average loss trade (USD)	-4.06
Largest profit trade (USD)	7.64
Largest loss trade (USD)	-5.18
Max consecutive wins	7 (USD 22.44)
Max consecutive losses	10 (USD -40.20)
AHPR (Daily)	1.0014 (0.14%)
GHPR (Daily)	1.0006 (0.06%)

3.2. Stability and resilience indicators

Figure 5 shows that the equity curve remained close to the balance curve throughout the test. This condition, measured using the equity stability index (ESI), indicates low floating losses and consistent position control as in (2). Similar stability patterns have been reported in capital-preserving algorithmic trading systems [21], [22].

$$ESI = 1 - \frac{\sum|Equity_t - Balance_t|}{\sum Balance_t} \tag{2}$$

In this experiment, the ESI value of 0.9672 indicates minimal floating losses and strong intraday capital control. The system's drawdown recovery behavior was further assessed using the rolling recovery ratio, defined in (3):

$$RollingRecovery_t = \frac{B_t - min(B_t - w{:}t)}{max(B_t - w{:}t) - min(B_t - w{:}t)} \tag{3}$$

where B_t is the balance at time t, and w is the window size (set to 30 in this case). As shown in Figure 6, the ratio oscillated significantly, indicating that recovery phases are not consistently sustained, revealing a structural limitation in the absence of adaptive exit reinforcement mechanisms [1], [23].

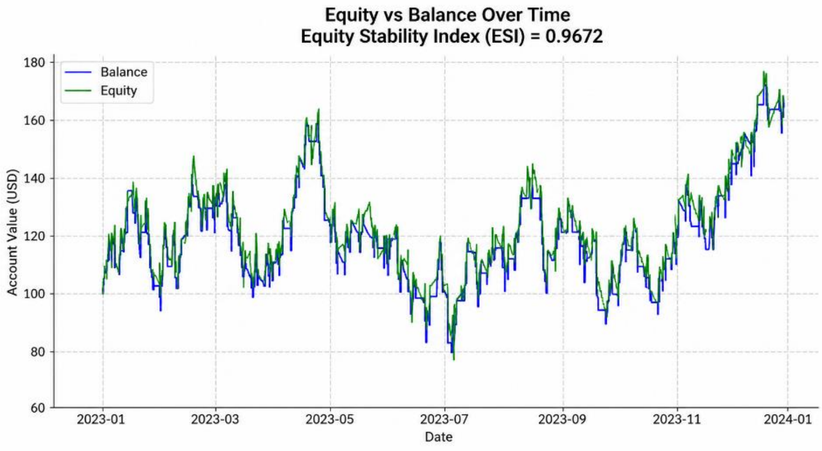

Figure 5. Equity and balance curves of the SARSA-FIS trading agent on EURUSD (M15), demonstrating high equity stability (ESI = 0.9672)

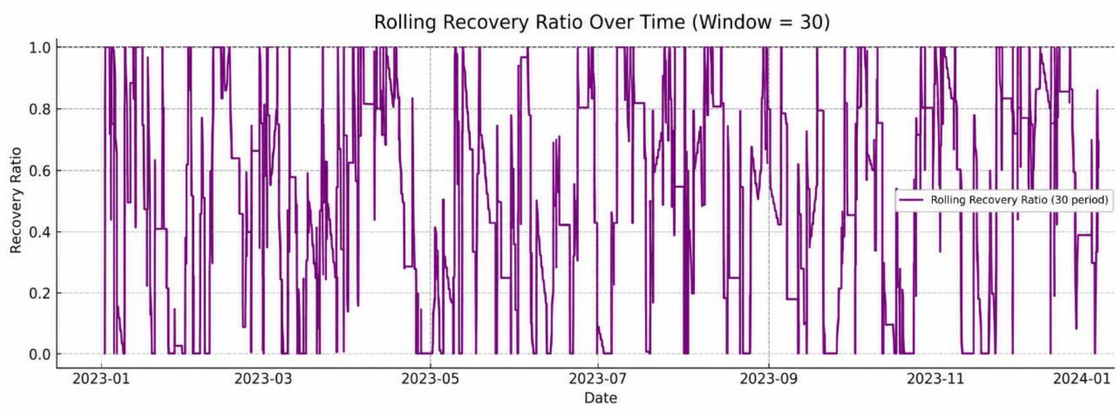

Figure 6. Rolling recovery ratio of the SARSA-FIS trading agent over 30-period windows, indicating the system's ability to recover from local drawdowns

3.3. Equity behavior and margin efficiency

To determine whether deviations between equity and balance were self-correcting, a lagged regression analysis was performed in (4).

$$(E_t - B_t) = \alpha + \beta.(E_{t-1} - B_{t-1}) + \epsilon_t \tag{4}$$

where E_t and B_t are the equity and balance at time t, respectively. A negative and significant β coefficient would indicate mean-reverting behavior, while a positive coefficient suggests persistence or divergence. The regression yielded a coefficient $\beta = 0.2401$ with a highly significant $p - value = 1.53\ x\ 10^{-25}$ $(p < 10^{-24})$. This suggests a conservative position holding style with delayed closure of floating trades.

The deposit load efficiency (DLE) metric was introduced to evaluate margin usage efficiency, as defined in (5).

$$DLE_t = \frac{\Delta Equity_t}{Deposit\ Load_t} \tag{5}$$

As seen in Figure 7, DLE showed sharp fluctuations, with occasional high efficiency followed by deep inefficiencies. This indicates that margin utilization is reactive rather than anticipatory, suggesting the absence of forward-looking capital allocation strategies [24], [25].

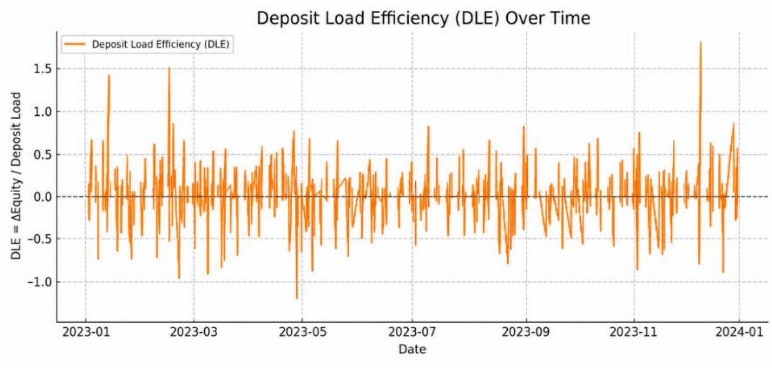

Figure 7. DLE of the SARSA-FIS trading agent over time, illustrating the relationship between margin utilization and equity gain

3.4. Structural change detection and event alignment

The CUSUM algorithm was applied to detect regime shifts in equity behavior, where deviations were flagged once cumulative residuals exceeded ±2 standard deviations. As shown in Figure 8, several structural shifts aligned with major macroeconomic events, including the silicon valley bank (SVB) collapse and the credit suisse acquisition. These observations highlight the agent's sensitivity to systemic volatility and its relevance for stress-responsive algorithmic trading systems [13], [20].

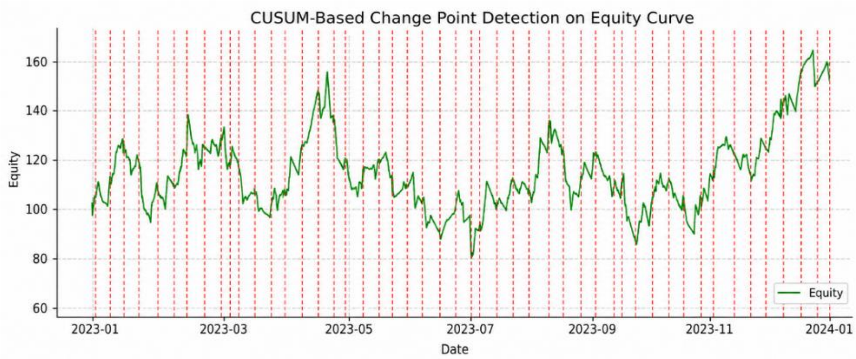

Figure 8. Change point detection on the equity curve using the CUSUM algorithm, highlighting regime shifts and structural transitions in trading performance

3.5. Discussion

The SARSA-FIS agent is a hybrid AI architecture tailored for interpretability and capital discipline in high-frequency forex environments. While the backtest showed a balanced win-loss ratio and micro-efficiency [26], the high drawdown (59.74%) and modest sharpe ratio (0.53) indicate resilience limits. This is consistent with prior findings highlighting RL sensitivity to volatility and the limitations of static fuzzy rule sets [27], [28]. The system maintained high ESI (0.9672), validating low floating exposure [22]. However, the rolling recovery ratio's volatility and lagged equity regression (β = 0.2401) suggest that once the system enters a drawdown phase, recovery is not sustained without external reinforcement.

Compared with traditional strategies such as moving-average crossovers, buy-and-hold approaches, and standalone fuzzy systems, the SARSA-FIS agent demonstrated more stable trading behavior and clearer decision logic across varying market regimes [24], [26]. Baseline models depend on fixed rules that often fail to adapt when volatility increases or structural conditions change [25]. In contrast, the hybrid SARSA-FIS framework combines adaptive feedback from RL with the interpretability of fuzzy inference [15], resulting in smoother trade continuity, improved responsiveness to regime shifts, and greater decision transparency. These findings demonstrate that the SARSA-FIS framework provides a more stable and interpretable alternative to conventional rule-based strategies, particularly under varying market regimes [13].

DLE analysis further exposed inconsistency in capital efficiency. Spikes of effectiveness were followed by deep inefficiencies, indicating reactive risk deployment rather than anticipatory behavior [24], [25]. These gaps reflect the need for adaptive margin control, real-time volatility assessment, and reward shaping mechanisms aligned with market regimes [23], [29]. Structural break detection via CUSUM confirmed strong correlations between macroeconomic shocks and equity inflection points. This aligns with prior work on the vulnerability of rule-based agents to systemic events [1], and supports the case for embedding regime-awareness into algorithmic systems. These findings confirm that the SARSA-FIS agent provides a structurally stable and explainable trading framework aligned with responsible AI principles [21]. However, enhancing robustness under volatile conditions requires the integration of volatility-aware policy adaptation, dynamic exit strategies, and real-time drawdown control mechanisms. This study demonstrates that sustainable algorithmic trading is not solely defined by profitability, but by stability, transparency, and controlled risk exposure under dynamic market conditions.

4. CONCLUSION

This study developed and tested a hybrid SARSA-FIS algorithmic trading system for the EURUSD currency pair, which met two key objectives: adaptability and interpretability. The model integrates RL with fuzzy logic to overcome the limitations of conventional rule-based and purely learning-based strategies in high-frequency forex environments. It also responds to the increasing demand for responsible and sustainable AI in financial systems. The SARSA-FIS agent, trained on M15 data (2020–2023) and tested on 2024, achieved moderate profitability (profit factor = 1.04), strong equity stability (ESI = 0.9672), and balanced trading outcomes. CUSUM analysis further demonstrated the model’s sensitivity to macroeconomic events, confirming that the agent can adapt to evolving market dynamics. However, a significant maximum drawdown (59.74%) and limited recovery behavior revealed challenges in maintaining robustness under volatile conditions.

These findings confirm that integrating fuzzy logic with RL enhances explainability and aligns algorithmic trading systems with responsible AI principles. The proposed framework demonstrates that transparency and adaptability can coexist within a reproducible, regulation-aligned trading environment, supporting ethical compliance and sustainable financial decision-making. From a practical perspective, such a system can assist traders, analysts, and regulators in evaluating automated decisions, improving auditability, and ensuring adherence to governance standards. Future research should focus on enhancing robustness under volatile conditions through volatility-sensitive reward functions, adaptive exit mechanisms, and real-time regime detection. Expanding this framework toward dynamic capital management, transaction cost optimization, and multi-agent coordination may further improve performance stability, scalability, and capital efficiency across diversified financial environments. This research contributes to the advancement of sustainable, interpretable, and ethical AI systems for forex trading and broader financial applications. Overall, this research contributes to the advancement of sustainable, interpretable, and ethical AI systems for forex trading and broader financial applications, reinforcing the integration of responsible AI principles into the design of intelligent financial technologies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, PM, upon reasonable request. The dataset is part of an ongoing dissertation project and is currently under consideration for patent protection. Partial data and reproducible materials are available at https://github.com/jonifat/SARSA-FIS-Sustainable-Trading-Framework.

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