

Robust trading in stochastic chaos: a hybrid fuzzy multi-expert approach

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Article Info

Article history:

Received Jun 28, 2025

Revised Jul 23, 2026

Accepted Aug 12, 2026

Keywords:

Chaos-driven forex

Fuzzy logic

Multi-expert system

Stochastic chaos

Trend filtering

ABSTRACT

Classical trend-following strategies often exhibit unstable performance in the EUR/USD foreign exchange market due to filter lag, noise-induced false signals, and abrupt regime transitions associated with chaotic price dynamics. This study proposes a hybrid fuzzy multi-expert framework that integrates bidirectional exponential filtering for low-latency trend extraction with a Mamdani-type fuzzy inference system that jointly evaluates quantitative trend indicators and qualitative information derived from economic news and textual forecasts. The proposed approach is evaluated on minute-level EUR/USD data over 10-, 25-, and 100-day test windows. Empirical results show that the fuzzy consensus mechanism improves robustness under non-stationary conditions. In a representative 25-day evaluation period, net profit increases from 182 to 560 pips, the win rate improves from 55% to 67%, and the maximum drawdown decreases from 118 to 38 pips. These findings suggest that incorporating linguistic uncertainty and sentiment-like contextual cues into technical trading signals can mitigate spurious trade activation and stabilize decision-making in stochastic and chaotic market environments, offering a practical route toward more resilient algorithmic trading systems.

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1. INTRODUCTION

The Forex market is known for its complexity and unpredictability, often displaying chaotic behavior and extreme volatility [1]–[4]. Under stochastic chaos, i.e., dynamically unstable price trajectories highly sensitive to initial conditions, traditional trend-following strategies struggle to remain effective [5]. Sudden market reversals and irregular fluctuations make standard linear models unreliable over time [6].

To overcome these issues, researchers have investigated chaos theory, adaptive control, and robust statistics [7], [8]. However, even advanced numerical models prove inadequate when abrupt sentiment-driven movements dominate the Forex market [9]–[11]. This highlights the need for more flexible decision-making tools capable of handling uncertainty in real-time trading. Fuzzy logic offers a strong framework for modeling decisions under uncertainty [12]. Using linguistic variables and fuzzy rules, it enables qualitative reasoning in automated systems [13]. These methods have proven useful in financial forecasting, improving decision reliability under uncertain conditions [14], [15].

In this paper, a hybrid fuzzy multi-expert system designed was introduced to enhance trend-following performance in chaotic Forex markets. The system combines technical analysis with fuzzy sentiment analysis based on economic news and textual forecasts [5], [16]. It uses bidirectional exponential filters for trend

detection and translates them into fuzzy linguistic terms, while a fuzzy sentiment module evaluates market mood via text mining.

These two modules are integrated via a Mamdani-type fuzzy inference system, executing trades only when both technical and fundamental signals align [5]. This hybrid approach reduces false signals and improves stability, especially during chaotic periods. Tests on EUR/USD data demonstrate that the system outperforms single-expert approaches in risk-adjusted returns and resilience to sudden market changes [17]. This work contributes to both fuzzy systems research and financial engineering by demonstrating how fuzzy logic can manage uncertainty in complex markets.

The remainder of this paper is as follows. Section 2 presents the theoretical background and experimental setup. Section 3 presents the experimental results and discussion. Finally, section 4 presents the conclusion and future research directions.

2. METHOD

2.1. Theoretical background

In standard stochastic frameworks, observed market data y_k is typically modeled as a combination of an underlying trend x_k and noise v_k .

$$y_k = x_k + v_k, k = 1, \dots, n$$

However, real-world financial markets exhibit chaotic behavior, where both components are non-stationary and highly volatile [18], [19]. Control-of-chaos research shows that unstable dynamics can be stabilized via control and feedback mechanisms [20], making traditional modeling assumptions inadequate and calling for tools that explicitly manage uncertainty.

To extract meaningful trends from noisy data, we employ exponential filtering.

$$x_k = x_{k-1} + \alpha(y_k - x_{k-1}), k = 2, \dots, n$$

Where $\alpha \in (0.001, 0.1)$ balances responsiveness and smoothness [21]. To reduce phase lag while preserving noise reduction, we apply bidirectional exponential smoothing: first in the reverse chronological direction, then forward to restore causality:

$$\tilde{y}_k^{(b)} = \alpha_b y_k + (1 - \alpha_b) \tilde{y}_{k+1}^{(b)}$$

$$\tilde{y}_k^{(f)} = \alpha_f \tilde{y}_k^{(b)} + (1 - \alpha_f) \tilde{y}_{k-1}^{(f)}$$

with $\alpha_{b,f} \in [0.005, 0.03]$ and window length $L = 20$ [5].

Filtered trends are then interpreted using fuzzy logic, translating numerical signals into linguistic variables such as "strong uptrend" or "no trend" [5]. Performance is measured using cumulative net profit.

$$\text{Eff}(S) = \sum_{j=1}^m (-1)^c (y_j(k_{out}) - y_j(k_{in})) p_j$$

Where k_{in} and k_{out} are entry and exit times, y is the price, p_j is position size, and c indicates trade direction (0 for buy, 1 for sell). A strategy is considered successful if it yields positive returns after transaction costs and slippage. In chaotic environments, results depend heavily on parameter stability and frequent recalibration.

Traditional trend-following strategies often generate misleading signals due to filter lag and fail to adapt to regime shifts [1], [5]. Even optimized parameters perform poorly out-of-sample, demonstrating the limitations of purely numeric approaches. However, when quantitative trend signals are combined with qualitative sentiment analysis, decision-making stability improves, especially during chaotic market phases [5].

2.2. Experimental setup

Despite improvements, residual instability remains in fully chaotic regimes. Future work will focus on refining fuzzy membership functions, exploring nonlinear fuzzy detectors, and extending the model to multi-asset correlations [17]. The system was evaluated on 1-minute EUR/USD open, high, low, close (OHLC) quotes from Finam at <https://www.finam.ru/> via trade application programming interface (Trade API), over three non-overlapping test windows: 10, 25, and 100 trading days. All data were preprocessed using linear interpolation for missing values and a rolling median filter (window = 5) for outlier removal. The

bidirectional filter used $\alpha_b = \alpha_f = 0.015$ with lookback $L = 20$, entry threshold $dy^* = 5$ pips, and exit threshold $dy^0 = -5$ pips. The sentiment module employed a pre-defined financial lexicon with three linguistic terms (bullish/neutral/bearish). The Mamdani inference engine applied nine rules with min/max operators and center-of-gravity defuzzification. Performance was measured by net profit (pips), win rate (%), and maximum drawdown (pips). The complete experimental protocol comprises the following steps:

- i) Data preparation: load 1-minute EUR/USD OHLC data for the specified test window. Apply linear interpolation to fill missing ticks. Remove outliers exceeding ± 3 standard deviations from the rolling median (window = 5).
- ii) Technical signal generation: apply bidirectional exponential filtering (section 2.1) with $\alpha_b = \alpha_f = 0.015$ and $L = 20$. Compute the smoothed price change dy over window L . Fuzzify dy into linguistic terms: "uptrend" if $dy > dy^*$, "downtrend" if $dy < -dy^*$, and "no trend" otherwise.
- iii) Sentiment signal generation: for each trading period, collect available economic news and textual forecasts. Apply lexicon-based classification to compute sentiment scores. Fuzzify scores into: "bullish," "neutral," or "bearish" based on predefined membership thresholds.
- iv) Fuzzy inference and trade execution: feed both fuzzified signals into the Mamdani inference engine. Apply the 9-rule base. Generate trading action: "buy" only if (trend is "uptrend" AND sentiment is "bullish"); "sell" only if (trend is "downtrend" AND sentiment is "bearish"); "hold" otherwise. Execute trades at the next available 1-minute open price.
- v) Position management and exit. Hold positions until either: i) the filtered trend crosses the exit threshold dy^0 (dynamic exit), or ii) a stop-loss is triggered (set at 75 pips for baselines; dynamic for TS-2 and TS-3). Record entry and exit prices, timestamps, and trade direction.
- vi) Performance evaluation. After completing all trades within the test window, compute net profit using $Eff(S) = \sum (-1)^c (y_j(k_{out}) - y_j(k_{in})) p_j$, win rate ($profitabletrades/totaltrades \times 100$), and maximum drawdown (largest peak-to-trough decline). Aggregate results across the three test windows (10, 25, and 100 days).

All parameter values, preprocessing choices, and evaluation criteria were fixed across all experiments to ensure consistent comparisons. Source code is available from corresponding author upon reasonable request.

3. RESULTS AND DISCUSSION

3.1. Baseline trend-following strategy

The baseline strategy employs a single exponential filter with fixed thresholds and exits. Table 1 summarizes its implementation. As shown in Figure 1, the baseline trend-following strategy with fixed stops (TS-1) generates frequent whipsaws in range-bound markets [1], [5], confirming that fixed-threshold rules fail in non-trending regimes.

Table 1. Baseline trend-following strategy with fixed stops

Component	Implementation	Performance	Optimization	Key limitations
Data preparation	1-min EUR/USD quotes 10/25/100-day windows - Preprocessing: interpolation, rolling-median outlier removal, time alignment	N/A	N/A	High-frequency noise affects signal quality
Entry condition	$ dy_{k-L:k} > dy^*$ dy is smoothed price change L is lookback window dy^* is threshold	Initial (10-day): +133 pips 57% win rate	Optimized params: $P^* = (0.01, 70, 10) \rightarrow$ + 532 pips, 69% win rate (in-sample)	Lags in sideways markets; late entries near reversals
Exit rules	Fixed take-profit / stop-loss = 75 pips	Effective in strong trends	None (static exits)	Fails in volatile/choppy conditions
smoothing	Exponential filter ($\alpha = 0.01$)	Reduces noise but adds lag	Tested $\alpha \in [0.005 - 0.03]$	Trade-off between responsiveness and false-signal rate
Optimization	Grid search: α (smoothing) $\in [0.005 - 0.03]$ L (window) $\in [10 - 100]$ dy^* (entry threshold) $\in [10 - 50]$	Best in-sample: +532 pips	Out-of-sample drop	Overfitting risk; poor generalization
Key insight	Fixed-threshold strategies fail in non-trending regimes	Works only in strong trends	Adaptive methods needed	Hybrid fuzzy logic proposed for robustness

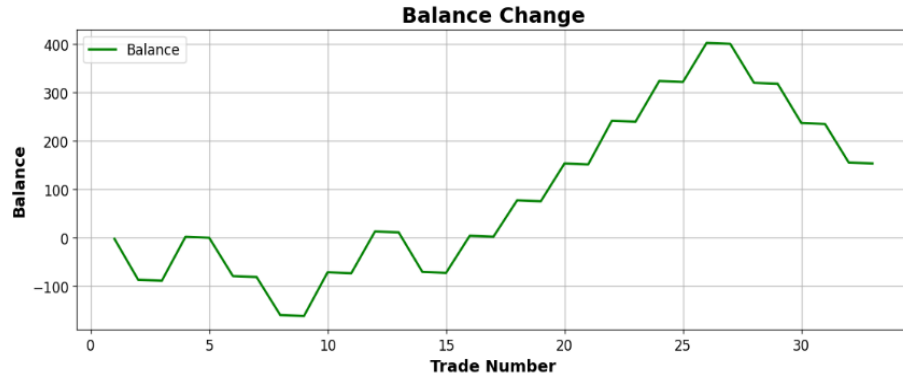


Figure 1. Effectiveness of the TS-1 trend strategy implementation

3.2. Adaptive trend strategy with flexible exit

Traditional trend-following strategies often use fixed take-profit (TP) and stop-loss (SL) levels, which perform poorly in chaotic markets. To improve adaptability, TS-2 was developed, a strategy that uses dynamic exit rules based on real-time trend strength (Table 2). After optimization, TS-2 improved net profit from 182 to 261 pips and win rate from 55% to 56% (Figure 2), but remained vulnerable to sudden reversals.

Table 2. Adaptive trend strategy with dynamic exits

Component	Fixed-threshold baseline	TS-2 innovation	Optimization results	Key limitations
Exit mechanism	Fixed TP/SL levels	Dynamic exits based on real-time trend strength	Reduced losses by 38% vs fixed exits in backtests	Still reactive to sudden reversals
Core parameters	Single threshold systems	4 adaptive parameters: α (smoothing) L (window) dy^* (entry) dy^o (exit)	Optimal set found: $P^* = (0.015, 20, 5, -5)$	High parameter sensitivity
Initial performance	N/A	25 pips net loss 43% win rate (default params)	Highlighted smoothing-induced delays	Weak in range-bound markets
Optimization	Manual tuning	Two-phase grid search: - Broad: $\alpha \in [0.005:0.03]$, $L \in [10:100]$ - Refined: $dy^* \in [5:25]$	Best results: 261 pips profit 56% win rate (20 min window, -5 exit threshold)	Computationally intensive
Market adaptation	Works only in strong trends	Better handles weakening trends via dy^o	Profitability improved by $10.4 \times$ after optimization	Fails in extreme volatility
Forward path	N/A	N/A	Proposed solution: Hybrid fuzzy logic + sentiment analysis	Requires non-numeric inputs

3.3. Dual-window trend strategy with fuzzy potential (TS-3)

TS-3 confirms trends across two independent time windows to reduce false entries. Table 3 presents the dual-window design. Optimized results in Figure 3 demonstrate that requiring concurrence across short (L_2) and long (L_1) windows halves the frequency of false entries and stabilizes returns during the 5-day test interval. From a practical perspective, TS-3 shows how combining multiple time horizons improves robustness — but it's not enough in highly unpredictable environments. Stability analysis was conducted by optimizing strategy parameters on a 100-day interval and testing them on subsequent 10-day intervals. Results revealed that parameters optimal for one regime frequently led to substantial losses in the next, highlighting the fragility of numeric-only approaches under chaotic dynamics. For example, the TS-1 strategy produced negative returns in all subsequent intervals after initial optimization, while TS-2 and TS-3 showed only marginal improvement. This instability underscores the necessity of hybrid decision frameworks that explicitly model regime shifts and incorporate qualitative, expert-based signals. This finding is consistent with the work [5] and is further supported by studies on the limitations of standard time-series models under non-stationary conditions [11].

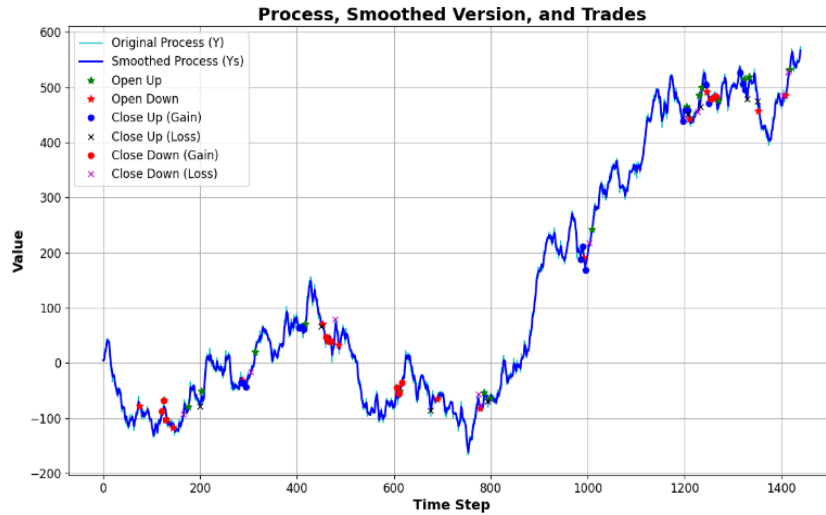


Figure 2. The TS-2 strategy with optimal parameters

Table 3. Dual-window trend strategy with prospective fuzzy integration

Component	Challenge	TS-3 innovation	Key limitations
Window length	Trade-off: – Short windows: noise sensitivity – Long windows: lag	Dual-window validation: trends must confirm in both timeframes (L_1, L_2).	Delayed entries during rapid trends; misses early trend phases.
Entry condition	False signals from single-window systems	Threshold-based: $ dy(k-L_1, k) > dy_1^*$ AND $ dy(k-L_2, k) > dy_2^*$	Still reactive; thresholds require frequent recalibration.
Initial performance	Subjective optimization	Full parameter set: $P = (\alpha, L_1, L_2, dy_1^*, dy_2^*, TP, SL)$	Overfitting risk; poor generalization to new data.
Optimization	Manual tuning ineffective	Grid search: – $\alpha \in [0.005:0.025]$ – $L_1 \in [10:50], L_2 \in [5:17]$	Computationally intensive; results degrade in non-stationary markets.
Performance	High false entries (TS-1/TS-2)	Improved filtering: – Fewer false signals – Better profit consistency	Vulnerable to chaotic reversals; early exits during volatility.
Key insight	Purely numerical strategies fail in chaos.	Forward path: hybrid fuzzy logic + sentiment analysis for adaptability.	Requires integration of qualitative data (e.g., news, events).

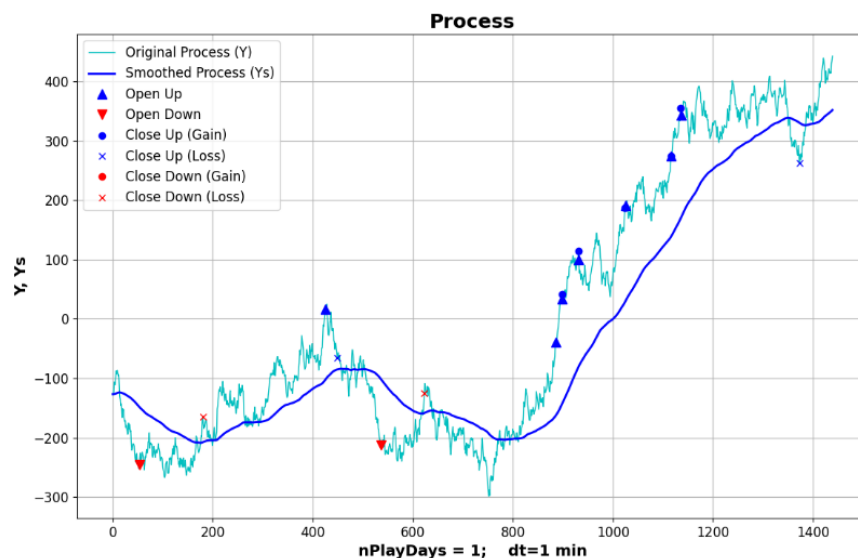


Figure 3. The TS-3 trend strategy with optimized parameters

3.4. Discussion

The comparative analysis across TS-1, TS-2, and TS-3 reveals a clear progression: adaptive exits and dual-window confirmation progressively reduce false signals and improve profitability. However, even the best numerical configuration (TS-3) remains vulnerable to chaotic reversals and parameter instability across regimes. The primary obstacle is the inherent trade-off between noise suppression and responsiveness — stronger smoothing introduces lag, while weaker filtering increases false triggers. Bidirectional exponential filtering mitigates this lag (Figure 4) but cannot eliminate it entirely.

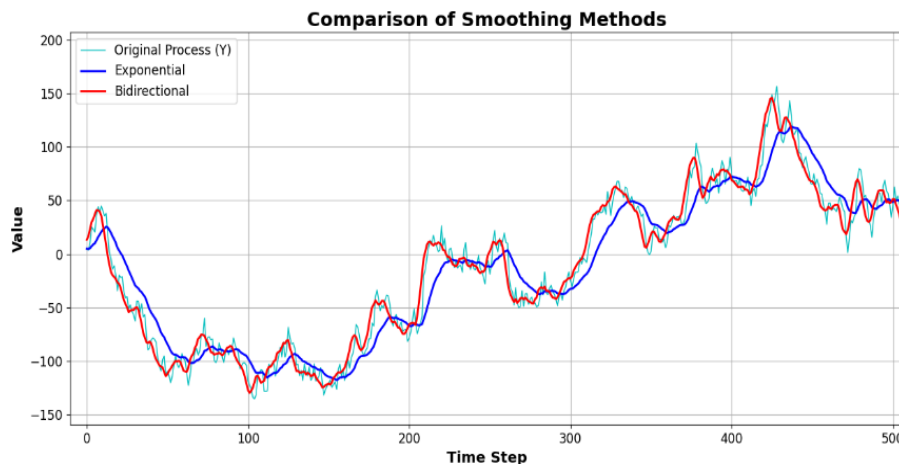


Figure 4. Comparison of conventional vs. bidirectional filtering

The fuzzy multi-expert system addresses this limitation by requiring alignment between technical trend signals and qualitative sentiment context. This consensus mechanism effectively filters out spurious trades that would otherwise be executed during noisy or range-bound periods. Empirical results on the 25-day window demonstrate substantial improvements over the best baseline: net profit increased from approximately 410 to 560 pips, win rate from 61% to 67%, and maximum drawdown decreased from 55 to 38 pips. These gains are attributed to the system's ability to defer decisions under conflicting signals and exploit only high-confidence opportunities, as illustrated in Figure 5.



Figure 5. Fuzzy multi-expert decision process

Nevertheless, the hybrid framework remains subject to certain limitations. First, the sentiment lexicon must remain relevant to current market narratives; abrupt policy shocks or structural breaks can degrade classification accuracy [22], [23]. Second, the fuzzy membership functions were pre-defined and may not adapt to evolving volatility regimes [24]. Future work will focus on online recalibration of fuzzy sets via clustering techniques, dynamic sentiment lexicon updates, and extension to multi-asset correlation signals to provide additional regularization during turbulent conditions [25].

4. CONCLUSION

The tests confirm that classical EUR/USD trend-following works only during sustained, well-defined trends lasting ≥ 5 –10 days. However, under chaotic conditions — marked by instability, random fluctuations, and sensitivity to external shocks — these methods become unreliable. Strategy performance breaks down quickly as market regimes shift, making previously optimal parameters ineffective. The central challenge remains the balance between noise suppression and prompt signal response: stronger smoothing invariably delays entry. Although advanced smoothing techniques like bidirectional filters help reduce lag, they cannot fully overcome the unpredictability of chaotic environments. Ex post parameter optimization may boost short-term results but often leads to overfitting, limiting generalization across changing conditions. For real-world traders, especially in volatile markets like Forex, this highlights the need to go beyond pure trend signals. Strategies should incorporate adaptive risk controls, diversified portfolios, and flexible exit rules to improve resilience. Despite their flaws, trend indicators remain useful when integrated into multi-expert systems based on fuzzy logic. The findings show that combining quantitative trend analysis with qualitative sentiment evaluation significantly improves decision-making under uncertainty. By translating economic news and expert opinions into linguistic variables, fuzzy systems filter misleading signals and enhance robustness. Despite the marked improvements, the hybrid fuzzy system is not immune to structural breaks or unforeseen shocks that can invalidate pre-trained sentiment or trend models. As future work, online adaptation of fuzzy membership functions, dynamic retraining of sentiment lexicons, and extension to multi-asset and cross-market signals are promising directions. Such developments would further enhance system resilience and adaptability under ever-evolving market conditions. Future research should explore nonlinear fuzzy strategies applied to multidimensional financial data. Capturing interdependencies across multiple assets using fuzzy inference could stabilize forecasts and improve reliability. Building on recent advances in chaotic time-series modeling, further studies should refine parameter adaptation, optimize preprocessing for fuzzy inputs, and benchmark hybrid systems against traditional approaches.

FUNDING INFORMATION

This research was supported by St. Petersburg State University, project ID: 121061000159-6.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Andrey Musayev	✓	✓	✓	✓	✓	✓			✓	✓	✓			
Dmitry Grigoriev		✓		✓	✓	✓	✓	✓	✓	✓		✓	✓	✓

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Finam at <https://www.finam.ru/> via Trade API.

REFERENCES

- [1] E. E. Peters, *Chaos and order in the capital markets: a new view of cycles, prices, and market volatility*. Hoboken, United States: John Wiley & Sons, 1996.
- [2] J. G. Williams and B. M. Williams, *Trading chaos: maximize profits with proven technical techniques*. Hoboken, United States: John Wiley & Sons, 2004.
- [3] T. Lux, "Stochastic behavioral asset-pricing models and the stylized facts," in *Handbook of Financial Markets: Dynamics and Evolution*, Elsevier, 2009, pp. 161–215, doi: 10.1016/B978-012374258-2.50007-5.

Robust trading in stochastic chaos: a hybrid fuzzy multi-expert approach (Andrey Musayev)

- [4] L. Rush and K. A. Blount, *Chaos theory*. Fort Collins, United States: Entangled Publishing, 2021.
- [5] A. Musayev and D. Grigoriev, "Multi-expert systems: fundamental concepts and application examples," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 2, pp. 336–348, 2022.
- [6] E. Schöll and H. G. Schuster, *Handbook of chaos control*. Weinheim, Germany: Wiley, 2007, doi: 10.1002/9783527622313.
- [7] P. J. Huber, *Robust statistics*. Hoboken, United States: John Wiley & Sons, 2004.
- [8] R. A. Maronna, R. D. Martin, V. J. Yohai, and M. S. -Barrera, *Robust statistics: theory and methods (with R)*. Hoboken, New Jersey: John Wiley & Sons, 2019.
- [9] G. Chen and X. Yu, *Chaos control: theory and applications*. Berlin, Germany: Springer, 2003.
- [10] Y. Bolotin, A. Tur, and V. Yanovsky, *Chaos: concepts, control and constructive use*. Berlin, Germany: Springer, 2009.
- [11] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time series analysis: forecasting and control*. Hoboken, United States: John Wiley & Sons, 2008, doi: 10.1002/9781118619193.
- [12] K. Du, F. Xing, R. Mao, and E. Cambria, "Financial sentiment analysis: techniques and applications," *ACM Computing Surveys*, vol. 56, no. 9, pp. 1–42, Oct. 2024, doi: 10.1145/3649451.
- [13] G. Fatouros, J. Soldatos, K. Kouroumalis, G. Makridis, and D. Kyriazis, "Transforming sentiment analysis in the financial domain with ChatGPT," *Machine Learning with Applications*, vol. 14, Dec. 2023, doi: 10.1016/j.mlwa.2023.100508.
- [14] A. Konar and D. Bhattacharya, *Time-series prediction and applications: a machine intelligence approach*. Cham, Switzerland: Springer, 2017, doi: 10.1007/978-3-319-54597-4.
- [15] A. Riva et al., "Addressing non-stationarity in FX trading with online model selection of offline RL experts," *ICAIF '22: Third ACM International Conference on AI in Finance*, 2022, pp. 394–402, doi: 10.1145/3533271.3561780.
- [16] R. Chauhan and H. Tyagi, "Text mining techniques for extraction and retrieval of information in research process," *International Journal of Research in Electronics and Computer Engineering*, vol. 7, no. 2, pp. 2693–2700, 2019.
- [17] I. Georgescu and J. Kinnunen, "Entropy and chaos-based modeling of nonlinear dependencies in commodity markets," *Entropy*, vol. 27, no. 9, Sep. 2025, doi: 10.3390/e27090955.
- [18] D. P. Feldman, *Chaos and dynamical systems*. Princeton, United States: Princeton University Press, 2019, doi: 10.2307/j.ctvc5pczn.
- [19] C. Oestreicher, "A history of chaos theory," *Dialogues in Clinical Neuroscience*, vol. 9, no. 3, pp. 279–289, Sep. 2007, doi: 10.31887/DCNS.2007.9.3/coestreicher.
- [20] S. Boccaletti, C. Grebogi, Y.-C. Lai, H. Mancini, and D. Maza, "The control of chaos: theory and applications," *Physics Reports*, vol. 329, no. 3, pp. 103–197, May 2000, doi: 10.1016/S0370-1573(99)00096-4.
- [21] E. S. Gardner, "Exponential smoothing: The state of the art," *Journal of Forecasting*, vol. 4, no. 1, pp. 1–28, Jan. 1985, doi: 10.1002/for.3980040103.
- [22] C. Truong, L. Oudre, and N. Vayatis, "Selective review of offline change point detection methods," *Signal Processing*, vol. 167, Feb. 2020, doi: 10.1016/j.sigpro.2019.107299.
- [23] M. Gupta, R. Wadhvani, and A. Rasool, "Comprehensive analysis of change-point dynamics detection in time series data: a review," *Expert Systems with Applications*, vol. 248, Aug. 2024, doi: 10.1016/j.eswa.2024.123342.
- [24] M. S. Islam, E. Hossain, A. Rahman, M. S. Hossain, and K. Andersson, "A review on recent advancements in Forex currency prediction," *Algorithms*, vol. 13, no. 8, Jul. 2020, doi: 10.3390/a13080186.
- [25] K. Kaczmarek, L. Dymova, and P. Sevastjanov, "Intuitionistic fuzzy rule-based evidential reasoning with application to the currency trading system on the Forex market," *Applied Soft Computing*, vol. 128, Oct. 2022, doi: 10.1016/j.asoc.2022.109522.

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