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Adaptive Optimization of Risk-Reward Ratio Leveraging Recurrent Neural Networks for Forex Trading

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Abstract

This study presents an innovative approach to risk management in algorithmic trading in the foreign exchange market (Forex). Instead of the traditional use of neural networks for price prediction (an approach with an extremely low signal-to-noise ratio), we employ a Long Short-Term Memory (LSTM) network to estimate the quality of a trading signal and subsequently dynamically calibrate the Risk-Reward Ratio (RRR). The proposed DA_AdaptiveRRR strategy thus represents an alternative approach: from "predict the price" to "evaluate signal quality and adapt exposure". Empirical testing on a diversified portfolio of currency pairs (EUR/USD, AUD/USD, GBP/JPY) during the 2023-2024 period demonstrated that the adaptive approach outperforms the standard benchmark (S2) by more than 1,400 pips and achieves positive returns on the majority of tested pairs. The cost-optimized static strategy (BD), which does not use a neural network, achieved the highest absolute profit (+3,140 pips), driven by strong trends in GBP/JPY, ahead of the fixed-RRR variant (FB, +1,490 pips). The study contributes to the field by demonstrating the first framework

that systematically combines LSTM with signal quality scoring for adaptive RRR management in the Forex market, an area that previously represented an identified research gap.

Keywords: Forex, Algorithmic Trading, Risk Management, Risk-Reward Ratio, LSTM, Signal Quality Scoring

1 Introduction

1.1 The Problem: Why Static Strategies Fail

Financial markets are inherently non-stationary systems. Market regimes change due to macroeconomic shocks, geopolitical events, changes in central bank monetary policy, or sudden shifts in liquidity. This inherent non-stationarity represents a fundamental challenge for algorithmic trading systems, which are typically calibrated on historical data reflecting different market conditions than those prevailing at the time of their deployment (Junior et al 2023; Olorunnimbe and Viktor 2022). For instance, applying multifractal detrended fluctuation analysis to high-frequency data on six major currencies, Aslam et al (2020) document a measurable decline in foreign exchange market efficiency during the initial COVID-19 outbreak, with heterogeneous effects across pairs (most pronounced for the Australian dollar), direct evidence that an exogenous shock can reshape the very statistical regime in which a trading system must operate.

Traditional approaches to risk management and money management often rely on **static parameters** or classical models such as the Kelly Criterion, which, however, requires an accurate estimate of the win probability, something that is difficult to achieve in noisy markets (Wu et al 2020; Jiang et al 2022). In an experimental review of Kelly- and Markowitz-based staking across horse racing, basketball and soccer, Uhrín et al (2021) show that the theoretical optimality of such formal strategies rests on the unrealistic assumption of knowing the true outcome probabilities, and that (given a fixed predictive model) the choice of position-sizing strategy itself has a decisive impact on realized profit, with an adaptive, risk-controlled fractional-Kelly variant proving the most robust in practice. Alternative approaches, such as fixed fractional methods, offer robustness but lack the ability to dynamically respond to changing opportunity quality (Choudhary et al 2025). This deficit leads to situations where:

- A strategy optimized for low volatility periods systematically fails during times of market turbulence.
- Conservative settings suitable for turbulent periods unnecessarily limit potential profits during calmer phases.
- A system with fixed parameters is unable to detect an upcoming regime change in time.

This problem can be metaphorically described as a **"Storm Ahead"** situation in which the trading system is unable to recognize an approaching change in time and adequately adjust its risk exposure.

1.2 Current State of Knowledge: Dominance of the Price Prediction Paradigm

The use of deep learning for financial market analysis is the subject of intensive academic research. Systematic literature reviews (Sezer et al 2020; Hu and Zhao 2021; Li and Sousa Bastos 2020) consistently show that **more than 90% of studies applying LSTM to financial markets focus primarily on predicting future price or direction of movement**. This trend is confirmed by the latest studies from 2025, which still dominate the area of "directional forecasting" (López-Herrera et al 2025), building on fundamental work in the field (Fischer and Krauss 2018). For instance, Abedin et al (2021) combine bidirectional LSTM networks with bagging-ridge regression to forecast the exchange rates of 21 currencies against the US dollar across the pre-pandemic and COVID-19 periods, evaluating their models solely through forecast-error metrics (RMSE, MAE, MAPE), a design emblematic of the field's continued focus on minimizing prediction error rather than on translating forecasts into risk-adjusted trading decisions.

A critical problem with this approach is that **statistical prediction accuracy often does not correlate with trading profitability** in a real environment. A model with higher prediction accuracy may generate worse risk-adjusted returns than a less accurate model if its errors are systematically correlated with periods of high volatility or if transaction costs are not adequately accounted for (Grądzki et al 2023; Olorunnimbe and Viktor 2022).

1.3 Research Gap: What Is Missing in the Literature

For rigorous mapping of the current state of research, a systematic review was conducted using the Consensus Deep Search platform, which analyzed a corpus of more than **1,070 peer-reviewed articles**. The results revealed a critical research gap, summarized in Table 1.

While there are efforts to integrate ML into the Kelly Criterion for position sizing in options strategies (Wu et al 2020; Wu and Chung 2018) or to use reinforcement learning for variable sizing (Jia et al 2021; Consigli et al 2024), there is no framework specifically focused on **supervised learning for signal quality scoring** and direct RRR management in Forex. Although there are initial attempts to predict the risk-reward ratio in general asset management (Yarbakhsh et al 2025), application to the microstructure of the FX market using Price Action signals remains unexplored. For instance, Wu et al (2022) build a settlement-date options trading system in which supervised classifiers (random forest, SVM) predict the win rate and a Kelly-criterion money-management module then sizes each position. Notably, they report that even barely acceptable predictions (around 50% precision) still yield steadily rising equity once Kelly-based sizing is applied, with their best ensemble attaining a profit factor

of 2.429 and a Sharpe ratio of 1.227, underscoring that disciplined position sizing, rather than raw predictive accuracy, is what ultimately drives profitability.

Table 1 Research Gaps Matrix

LSTM Application Area	FX Studies	Status
Price / Direction Prediction	>50 studies	Saturated
Kelly Criterion + ML Optimization	3-5 studies	Focused on options/stocks
Volatility / Risk Forecasting	1-2 studies	Partially explored
Signal Quality Scoring	**0 studies**	**Identified gap**
Adaptive RRR Management	**0 studies**	**Identified gap**

Source: Systematic review via Consensus Deep Search (N=1,070), December 2025.

As the conclusion of the systematic review states: *"There are very few studies that explicitly treat LSTM as a dedicated 'signal quality evaluator' or as a direct controller of risk-reward ratios in FX."*

1.4 Proposed Methodological Framework

This study adopts a fundamentally different approach. **Instead of attempting to predict future prices, we use an LSTM network to estimate trading signal quality**, that is, to predict the probability that a given Price Action signal will lead to a successful trade. This probability then serves as input for dynamic calibration of RRR parameters in real-time.

The proposed DA_AdaptiveRRR methodology represents a shift in the approach to risk management, as contrasted in Table 2:

Table 2 Conceptual Shift in the Approach to Risk Management

Traditional Approach	Our Approach
Predict the price	Evaluate signal quality
Trade based on prediction	Adapt risk exposure
Fixed RRR / Kelly Criterion	Dynamic RRR based on confidence
Static SL/TP	Adaptive SL/TP

The system functions as an **intelligent filter of market conditions**: during times of high uncertainty, it automatically reduces exposure, while during times of high confidence, it allows maximization of potential profit.

1.5 Practical Implications

This approach has broader implications beyond purely speculative trading:

For hedging and foreign exchange risk management: The system's ability to detect deteriorating signal quality (and thus implicitly an approaching market regime change) represents a valuable tool for hedging strategies. Early detection of a "storm

ahead" situation allows portfolio managers to preventively adjust exposure before a market shock materializes.

For practitioners and portfolio managers: The model provides an interpretable output (Confidence Score) that can be directly used for risk management decisions, unlike "black box" prediction models.

1.6 Research Question

The aim of this study is to answer the research question: *Can dynamic adaptation of Risk-Reward Ratio controlled by a neural network that estimates trading signal quality outperform traditional static models in an environment of changing market regimes, when real transaction costs are accounted for?*

2 Methodology

The methodology of this study was designed with primary emphasis on **scientific integrity and conservative estimation of results**. In response to justified criticism of previous studies that often neglect market microstructure aspects and real transaction costs (Junior et al 2023; Grądzki et al 2023), we implement several methodological pillars.

2.1 Data and Justification for Market Selection

Data Source: Historical tick data from Dukascopy Bank SA (a regulated Swiss banking entity).

Specifications:

- Type: 1-minute (M1) OHLCV data aggregated to hourly (H1)
- Price model: Separate BID and ASK prices (realistic spread)
- Currency pairs: EUR/USD, AUD/USD, GBP/JPY

Currency Pair Selection: The selection of test instruments was not random but was designed to cover different market microstructures and volatility clusters according to current literature:

1. **EUR/USD (Major):** Chosen as a benchmark of global liquidity and efficiency. Literature confirms that USD-based pairs exhibit the lowest price impact and highest market depth (Ranaldo and De Magistris 2022).
2. **AUD/USD (Commodity Currency):** Chosen as a representative of currencies tied to commodity cycles. Studies show a strong correlation between AUD and global commodity prices, creating specific trend characteristics different from EUR/USD (Liu et al 2020; Devereux and Smith 2021).
3. **GBP/JPY (Carry Trade Cross):** Chosen for its high volatility and sensitivity to interest rate differentials. This pair is often associated in the literature with carry trade mechanisms and susceptibility to "crash risk" scenarios during increases in global risk aversion (Abankwa and Blenman 2021; Iseringhausen 2020).

Time Split:

- In-Sample (Training): 2021-2022
- Out-of-Sample (Test): 2023-2024 (strictly separated data)

2.2 Cost Model

Unlike many theoretical studies, our model explicitly includes transaction costs.

Net Trade Profit:

$$\text{Net_PnL} = \text{Gross_PnL} - \text{Spread} \tag{1}$$

Spread: Realistic values derived from market conditions:

- EUR/USD: 1.0 pip
- AUD/USD: 1.5 pip
- GBP/JPY: 2.3 pip

2.3 Definition of Tested Strategies

For objective evaluation of the adaptive approach's contribution, five strategies of varying complexity were implemented (Table 3):

Table 3 Overview of Tested Strategies

Abbr.	Name	Description	RRR	SL/TP
S2	Standard 2:1	Baseline with fixed RRR 2:1	Fixed 2.0	Static
FB	FixBestRRR	In-Sample optimized params	Fixed (opt.)	Static
DR	DynamicRRR	Exponential calibration	Dynamic	Dynamic
DA	AdaptiveRRR	LSTM + sigmoid calibration	Adaptive	Adaptive
BD	BestDynamicNoNN	Optimized NN-strategy params, NN switched off	Fixed (opt.)	Static

Detailed Strategy Definitions:
S2_Standard (Benchmark):

- Risk-Reward Ratio: fixed 2:1 (TP = 2× SL)
- Stop Loss: fixed value derived from ATR (Average True Range)
- Without any adaptation to market conditions, it serves as a baseline for comparison.

FB_FixBestRRR:

- RRR optimized on In-Sample data (2021-2022) using grid search.
- Parameters frozen for Out-of-Sample testing.
- Represents the best fixed-RRR static strategy.

DR_DynamicRRR:

- RRR changes according to an exponential function of LSTM prediction.
- Formula:

$$\text{RRR} = \text{base} \cdot \exp\left(k \cdot (p_{\text{lstm}} - 0.5)\right) \tag{2}$$

where k is the exponential sensitivity parameter and base is the baseline RRR.
- Tests the hypothesis of whether dynamics itself adds value without advanced calibration.

DA_AdaptiveRRR (proposed model):

- LSTM network estimates the probability of signal success (p_{lstm}).
- Uses sigmoid calibration for transforming prediction to RRR.
- Formula:

$$\text{RRR} = 0.8 + 3.2 \cdot \sigma\left((p_{\text{lstm}} - 0.5) \cdot \text{sensitivity}\right) \tag{3}$$

  where $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function.
- Includes adaptive SL and TP.

BD_BestDynamicNoNN (neural-network ablation):

- Uses the same optimized parameters found for the dynamic neural-network strategies (DR/DA), but with the neural network switched off, so the RRR remains fixed.
- Isolates the contribution of the neural network: identical optimized parameters, only the adaptive NN component removed.
- Serves as a strong static benchmark. The term "Dynamic" in its name refers to the origin of its parameters (the dynamic-strategy optimization), not to its run-time behavior, which is static.

2.4 Neural Network as Signal Quality Classifier

At the core of the DA_AdaptiveRRR system is an LSTM network that **does not predict future price but performs classification of trading signal quality**. For network architecture, we draw from standard recommendations for recurrent networks in finance (Yu et al 2019), but with a modified objective function.

Task Formulation: The network output is a probability p_{lstm} in an interval representing the estimated chance of success for a given Price Action signal.

Key Empirical Finding (Confidence Score): Analysis of results revealed a fundamental insight: **the model does not predict the direction of price movement but the quality of the Price Action signal**. Extreme values on **both sides of the spectrum** (both high and low) indicate a quality signal, while values close to 0.5 signal that the model cannot decide, and thus the signal is of low quality. The confidence score C is defined as the absolute deviation of the prediction from the neutral value 0.5, scaled to the unit interval:

$$C = 2 \cdot |p_{\text{lstm}} - 0.5| \tag{4}$$

Thus a neutral prediction ($p_{\text{lstm}} = 0.5$) yields $C = 0$, while extreme predictions ($p_{\text{lstm}} = 0.85$ or $p_{\text{lstm}} = 0.15$) yield $C = 0.70$. Table 4 summarizes how the LSTM output maps to confidence levels and the corresponding RRR action.

Table 4 Interpretation of LSTM Output

LSTM prediction (p_{lstm})	Confidence (C)	Interpretation	Action
0.85+	0.70+	High confidence (bullish)	Aggressive RRR
0.15-	0.70+	High confidence (bearish)	Aggressive RRR
0.40-0.60	0.00-0.20	Uncertainty, indecision	Conservative RRR

2.5 Dynamic RRR Calibration and Sigmoid Transformation

Risk-Reward Ratio is dynamically adjusted using a sigmoid transformation function. The choice of this function is not random. Although logistic regression is often used in trading for binary "success/failure" classification (Hruška 2014), our application utilizes the mathematical properties of the sigmoid curve for continuous risk calibration. The sigmoid effectively maps scores into a bounded probability interval (Kravets et al 2024), which is key for establishing robust decision thresholds and dampening noise around the neutral point (Bokov and Antonenko 2020).

While the exponential function (used in the DR strategy) reacts aggressively to any deviation, our sigmoid calibration (DA) functions as a filter:

1. **Noise Dampening:** Small deviations from 0.5 (where uncertainty is highest) are transformed into minimal RRR changes.
2. **Extreme Saturation:** At very high confidence, the function safely saturates at the maximum allowed RRR (here 4.0), preventing "overfitting" to isolated extreme predictions.

2.6 Conservative Validation

Worst-Case Scenario for SL/TP Conflict: When using hourly candles, a situation arises where price movement within a single candle may hit both Stop Loss and Take Profit. Without access to tick data, it is impossible to determine with certainty which level was hit first. **Our approach:** We always assume a loss (SL first), thereby **deliberately underestimating** strategy results. Any real result can only be better.

3 Results

Empirical testing was conducted on out-of-sample data (2023-2024).

3.1 Overall Strategy Performance

Table 5 summarizes the aggregated performance across all five strategies.

All pip values are rounded to the nearest pip. Aggregate figures are computed from unrounded trade-level data, so per-pair sums may differ by about one pip.

Key Observations:

1. **BD_BestDynamicNoNN** achieved the highest absolute profit, likely due to strong trends in GBP/JPY.

Table 5 Aggregated Strategy Performance (Out-of-Sample 2023-2024, 3 pairs)

Strategy	Trades	Win Rate	Net Profit (pips)	Profit Factor
BD_BestDynamicNoNN	889	32.3%	**+3,140**	**1.14**
FB_FixBestRRR	722	27.0%	+1,490	1.04
DA_AdaptiveRRR	1,113	31.5%	+356	1.00
DR_DynamicRRR	1,206	36.2%	-411	0.98
S2_Standard	1,474	33.4%	-1,088	0.91

2. **DA_AdaptiveRRR** proved robust among the neural-network-based strategies (profitable on 2 out of 3 pairs) and **outperformed the standard benchmark (S2) by more than 1,400 pips**.
3. **The difference between DA (+356) and DR (-411)** confirms the benefit of sigmoid calibration over simple exponential.

Fig. 1 shows the cumulative equity curves of all strategies, and Fig. 2 shows the corresponding drawdown profile.

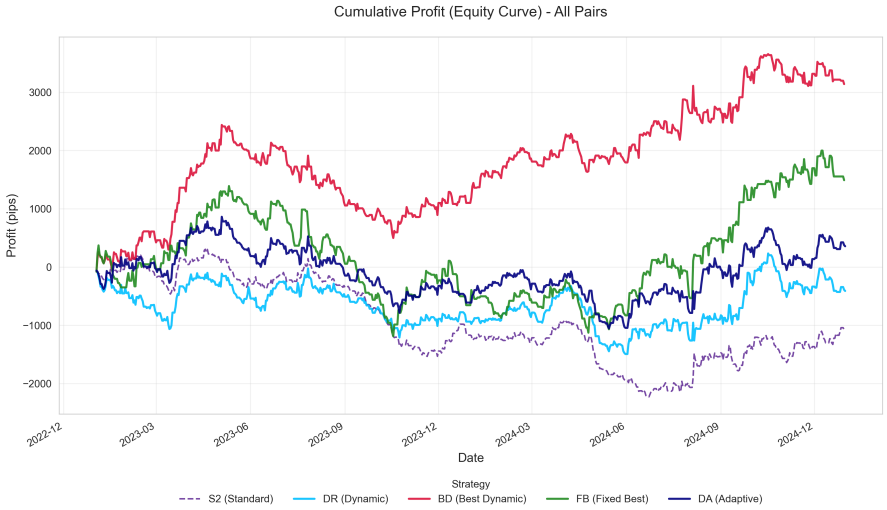


Fig. 1 Cumulative Equity Curves of All Strategies (Aggregation of 3 pairs, 2023-2024). BD (red) achieves the highest absolute profit, followed by FB (green). DA (dark blue) shows a comparatively stable but lower trajectory, while the S2 benchmark (dashed purple) ends in deep loss

3.2 Performance by Currency Pair

Table 6 reports the detailed performance by currency pair.

3.3 Robustness Analysis

Table 7 shows the number of profitable pairs by strategy.

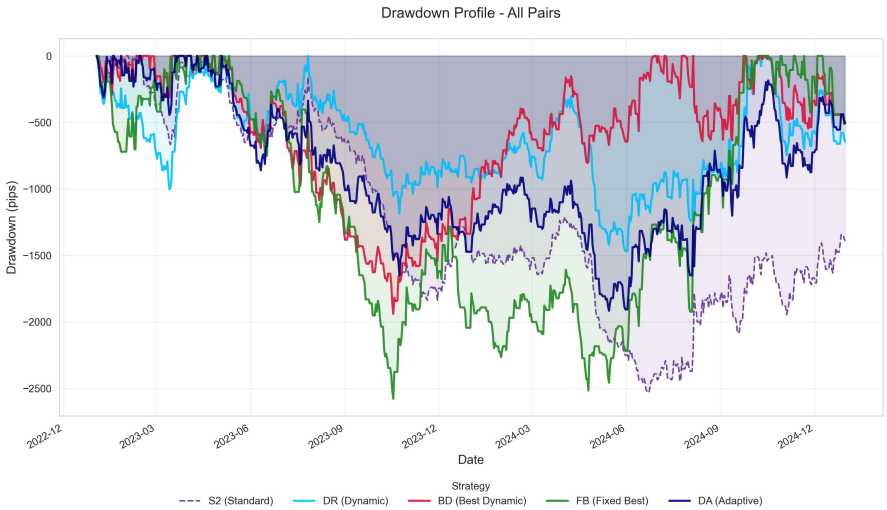


Fig. 2 Drawdown Profile of All Strategies (Aggregation of 3 pairs, 2023-2024). DA (dark blue) maintains drawdown within controlled limits. FB (green) experiences deep drawdown in the first half of 2024 but subsequently recovers

Table 6 Detailed Performance by Pair

Pair	Strat.	Trades	Win%	Profit	PF
EUR/USD	FB	261	26.8%	-89	0.98
EUR/USD	DA	402	32.1%	+115	1.02
EUR/USD	DR	436	35.6%	-111	0.98
EUR/USD	S2	531	30.3%	-1,126	0.78
EUR/USD	BD	311	33.1%	+339	1.06
AUD/USD	FB	220	25.5%	-19	1.00
AUD/USD	DA	353	29.8%	-365	0.93
AUD/USD	DR	376	34.8%	-261	0.95
AUD/USD	S2	467	34.5%	-359	0.92
AUD/USD	BD	291	31.3%	+488	1.10
GBP/JPY	FB	241	28.6%	+1,598	1.13
GBP/JPY	DA	358	32.7%	+606	1.05
GBP/JPY	DR	394	38.1%	-40	1.00
GBP/JPY	S2	476	35.3%	+396	1.04
GBP/JPY	BD	287	32.4%	**+2,313**	**1.18**

Table 7 Number of Profitable Pairs by Strategy

Strategy	Profitable Pairs	Total Pairs	Robustness
BD_BestDynamicNoNN	3	3	**100%**
DA_AdaptiveRRR	2	3	67%
FB_FixBestRRR	1	3	33%
S2_Standard	1	3	33%
DR_DynamicRRR	0	3	0%

Interpretation: BD_BestDynamicNoNN (static, without a neural network) is profitable on all three pairs, while DA_AdaptiveRRR is **the most robust among the neural-network-based strategies** (profitable on 2 out of 3 pairs).

4 Discussion

4.1 GBP/JPY Dominance and the Carry Trade Phenomenon

The most striking empirical finding is the **concentration of profits in the GBP/JPY pair**. This phenomenon cannot be attributed solely to chance but has a clear economic basis in the **Carry Trade** mechanism. The significant interest rate differential between the British pound and Japanese yen creates strong, persistent trends (Rubaszek et al 2024).

Literature confirms that pairs with high interest rate differentials exhibit specific volatility dynamics, where calm periods of profitable trends alternate with sudden asymmetric shocks and forced position liquidations (Cho et al 2019; Hambuckers and Ulm 2023). Global volatility is a key risk factor that has historically eroded profits of strategies based on interest rate differentials (Menkhoff et al 2012; Zeng 2023). Our static strategies (BD and FB) captured this trend effectively, with BD profiting the most, but without an adaptive component, they remain vulnerable to these "crash risk" scenarios. This vulnerability echoes the walk-forward experiments of Musaev and Grigoriev (2025) on EUR/USD, in which trend-management strategies optimized on one observation interval systematically lose effectiveness (and frequently turn into losses) on subsequent unseen intervals owing to the market's inherent instability, leading the authors to conclude that standalone trend strategies are unsuitable for stable asset management in chaotic conditions and are better embedded within adaptive, hybrid (multi-expert) decision systems. Fig. 3 shows the equity curves on the GBP/JPY pair.

4.2 Value of the Adaptive Approach

On this out-of-sample data the naive benchmark S2 (fixed 2:1 RRR) is loss-making (net -1,088 pips). The neural-network-adaptive DA strategy turns this loss into a profit (net +356 pips) and at the same time reduces the aggregate maximum drawdown by 27% (from 2,545 to 1,866 pips), while also outperforming the alternative neural-network variant DR. Relative to the standard benchmark and to a poorly calibrated dynamic rule, signal-quality-driven RRR adaptation therefore adds measurable value. This is consistent with the conclusions of Bucci (2020), who shows that neural networks (including LSTM) outperform traditional econometric models in predicting volatility and risk, a key input for our adaptive model.

A more demanding comparison, however, tempers this conclusion. A fully cost-optimized static strategy (BD/FB) attains a higher risk-adjusted return in the strongly trending 2023-2024 regime, with a net-profit-to-maximum-drawdown ratio of 1.61 for BD against 0.19 for DA. In terms of drawdown control, DA does offer a genuine advantage over the standard and fixed-RRR benchmarks (DA 1,866 pips, below FB 2,486 pips and S2 2,545 pips), but not over BD, whose maximum drawdown of

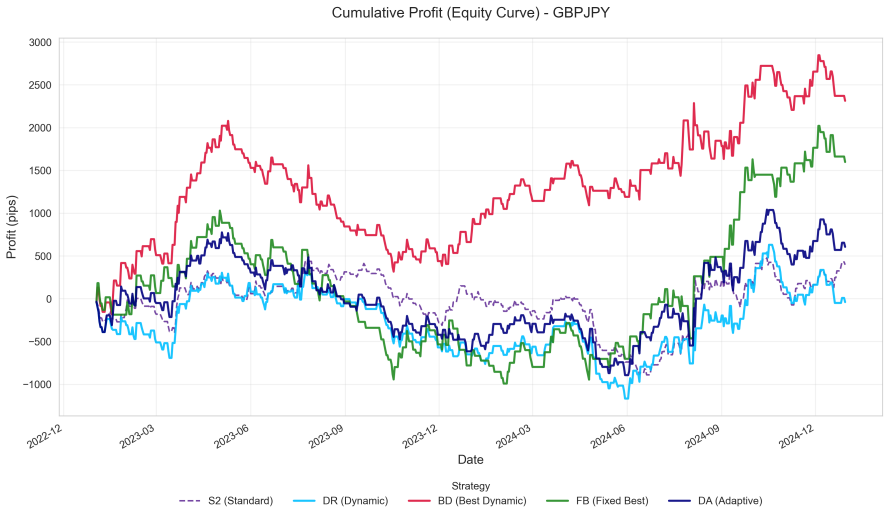


Fig. 3 Equity Curves on GBP/JPY (2023-2024). BD (red) profited the most, followed by FB (green). The strong upward move from mid-2024, driven by the carry-trade mechanism, allowed strategies with higher target levels (higher RRR) to capture larger gains

1,952 pips is comparable to DA's while its risk-adjusted return is markedly higher. The contribution of neural adaptation is thus promising but, at the present scale of data, not decisive, a finding that directly motivates the dynamic, reinforcement-learning-based approach developed in our follow-up work. Table 8 compares the fixed-RRR strategy FB with the adaptive strategy DA.

Table 8 Comparison of FB vs. DA

Metric	FB_FixBestRRR	DA_AdaptiveRRR	Interpretation
Total Profit	+1,490	+356	FB higher
Profitable Pairs	1/3 (33%)	2/3 (67%)	**DA more robust than FB**
EUR/USD Profit	-89	**+115**	**DA profitable while FB loses**

4.3 Sensitivity to Transaction Costs

The profitability of the adaptive strategy is sensitive to transaction costs. Before costs (gross), DA is profitable on all three pairs: EUR/USD +517 pips, AUD/USD +164 pips and GBP/JPY +1,429 pips. After a realistic spread is applied, it remains profitable on two of the three pairs. On AUD/USD the modest gross gain of +164 pips is entirely consumed by spread costs (1.5 pips across 353 trades), turning into a net loss of approximately -365 pips, whereas EUR/USD and GBP/JPY stay net positive. Strategies that trade more frequently accumulate a larger total spread and are therefore penalized more heavily. This sensitivity is a further reason to optimize

trading rules explicitly under a cost constraint, a direction we pursue in subsequent work.

4.4 Difference DA vs. DR: Why Sigmoid Works

The difference between DA (+356 pips) and DR (-411 pips) amounts to **767 pips**. This difference is consistent with the view that "dynamics" alone is not sufficient if not properly calibrated. Sigmoid transformation (DA) proved to be key because it effectively filters noise in neural network predictions, which is consistent with the theory of classifier stability (Wang 2025).

4.5 Contextualization in Literature and Money Management

Our approach can be viewed as a modern alternative to classical position management methods. As discussed in the introduction, the traditional Kelly Criterion, which maximizes long-term growth, is in practice highly sensitive to inaccuracies in win probability estimation, and although some studies refine these probabilities using machine learning or employ "fractional Kelly" methods to reduce drawdowns, our model bypasses the need for fixed sizing.

Instead, we use signal quality prediction to adjust the **Risk-Reward Ratio**. This differentiates us from pure reinforcement learning (RL) approaches that optimize the entire portfolio as "fixed-mix" strategies (Consigli et al 2024; Choudhary et al 2025). Our supervised learning approach is more transparent and focused on the microstructure of individual trades, which corresponds to the findings of Yarbakhsh et al (2025) on the benefits of RRR prediction, but with unique application to Forex.

Response to Junior et al (2023): The authors identified non-stationarity as the main cause of deep learning model failures. Our methodology directly addresses this problem through dynamic RRR adaptation.

4.6 Economic vs. Statistical Significance

For rigorous evaluation of results, two statistical tests were conducted comparing the performance of the adaptive strategy DA versus the benchmark S2:

Paired t-test of daily returns: p-value = 0.40

Bootstrap test of Sharpe Ratio: p-value = 0.24

Neither test demonstrated statistical significance at the conventional level $\alpha = 0.05$. However, this finding is not inconsistent with the practical value of the strategy.

Current literature in the field of financial econometrics and algorithmic trading increasingly distinguishes between **statistical and economic significance**. As noted by Karhunen (2019) and López-Herrera et al (2025), trading strategies in noisy markets can exhibit substantial economic benefit (profit, Sharpe ratio) even when standard statistical tests fail to reject the null hypothesis due to high return variability.

Furthermore, the factor of non-stationarity must be considered. Musaev and Grigoriev (2025) point out that financial markets exhibit chaotic behavior and frequent regime changes, which undermines the validity of long-term statistical tests on stationary data. Our result (an economic difference of more than 1,400 pips with lower

statistical power) is consistent with the nature of "swing" strategies that generate profit in concentrated market movements, not in every observation. Table 9 summarizes economic versus statistical significance.

Table 9 Economic vs. Statistical Significance

Metric	Value	Interpretation
Economic difference DA vs S2	+1,444 pips	Practically very significant
t-test p-value	0.40	Statistically not significant
Bootstrap p-value	0.24	Statistically not significant
Conclusion	-	Economic significance with low statistical power

5 Conclusion

This study aimed to answer the question of whether dynamic adaptation of risk parameters, controlled by an LSTM network estimating signal quality, can outperform traditional static models in an environment of non-stationary markets.

The conducted research leads to the following conclusions:

1. **Absolute Performance:** The fully cost-optimized static strategy BD_BestDynamicNoNN achieved the highest absolute profit (+3,140 pips), ahead of the fixed-RRR variant FB (+1,490 pips), confirming that during periods of strong trends (GBP/JPY 2023-2024) static strategies can excel.
2. **Risk-Adjusted Performance:** On a risk-adjusted basis the static benchmark led in this trending regime, with a net-profit-to-maximum-drawdown ratio of 1.61 for BD versus 0.19 for DA, indicating that the benefit of neural adaptation, while promising, is not decisive at the present scale of data and motivating the dynamic reinforcement-learning approach developed in our subsequent work.
3. **Robustness and Diversification:** Among the neural-network-based strategies, the proposed DA_AdaptiveRRR was the most robust (profitable on 2 out of 3 pairs), although the static BD benchmark was profitable on all three.
4. **Benchmark Outperformance:** DA_AdaptiveRRR **outperformed the standard benchmark (S2) by more than 1,400 pips**.
5. **Methodological Contribution:** The study presented the first framework that systematically combines LSTM with signal quality scoring for adaptive RRR management in the Forex market, an area that previously represented an identified research gap in the literature.
6. **Importance of Calibration:** The difference between DA and DR confirms that the method of transforming LSTM prediction to RRR factor is critical. The sigmoid approach outperforms the exponential one by 767 pips.
7. **Statistical Significance:** Although the economic significance of the difference is evident (>1,400 pips), statistical tests (t-test p=0.40, bootstrap p=0.24) did not reach conventional significance levels, suggesting that above-average performance depends on market regime and requires further research in regime detection.

In direct answer to the research question: under the tested conditions and the two-layer LSTM configuration, the neural-network-based adaptive RRR (DA) did not outperform the optimized static benchmarks (BD and FB). It did, however, outperform the naive 2:1 benchmark (S2) and the weaker exponentially calibrated dynamic variant (DR), indicating a conditional rather than decisive benefit and motivating the dynamic reinforcement-learning approach pursued in our subsequent work.

Testing was deliberately conducted on three representative currency pairs covering different market characteristics (major, commodity, carry trade). The 2023-2024 period was characterized by strong trends, particularly in GBP/JPY. The model in its current version does not explicitly distinguish between market regimes (trending vs. ranging), which represents an area for further research and potential performance improvement.

A promising direction for adaptive systems is not the search for a "holy grail" of price prediction, but intelligent, AI-assisted adaptation to the constantly changing market environment.

Statements and Declarations

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Competing Interests. The authors have no competing interests to declare that are relevant to the content of this article.

Data Availability. The data that support the findings of this study are publicly available from Dukascopy Bank SA via the Dukascopy trading platform, including in demo mode.

Code availability. The code used in this study is available from the corresponding author on reasonable request.

Declaration of Generative AI and AI-assisted technologies in the writing process. During the preparation of this manuscript, the authors used AI-based language models to assist with drafting, language editing, and formatting of the text. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the scientific content and conclusions of the publication.

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