The 3mTSHSUHC.*rp3*: Metric Threshold and Minimum Bars Apart Analysis of Three-minute Timeframe Stoporder Hedging Strategy Using Heatmap Candles

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Abstract

This study represents the third phase in developing the 3mTSHSUHC model, advancing from version 1 and stress testing to version 2. Previous versions relied solely on the *metric threshold* parameter to generate hedge signals. In this study, an additional condition—*minimum bars apart*—is introduced, so a hedge signal is triggered only when both conditions are satisfied. The goal is to identify the optimal ranges of *metric threshold* ($y \sim 0, 0.05, \ldots, 1$) and *minimum bars apart* ($x \sim 1, 2, \ldots, 500$), evaluating 10,521 possible pairs to find regions generating favorable *winrate%*, *return%*, *max drawdown%*, and *profitability score* outcomes.

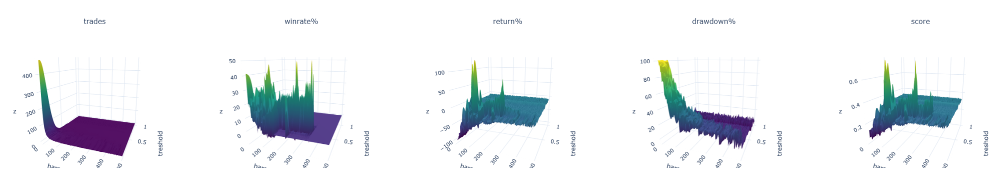

Figure 1: *The x-bars apart, y-metric threshold, and respective z-variables: trades, winrate, return, drawdown, and profitability score performance*

The 3mTSHSUHC.*rp3* model undergo in automated backtest with doubled stress parameters to simulate harsh market conditions, worse than live environment quotes: a spread of 0.60 price units, random slippage of 0–2 price units, and a commission of 2%. The account exposure per trade is 5%, within an intraday profile made of 500 3m-timeframe candles. Results indicate that restricting *metric threshold* and *minimum bars apart* near ($y \approx 40, x \approx 320$) yields 4,160 optimal pairs, a 60.5% improvement over using all combinations. Within this region, the top 10 performing pairs were identified, where *metric threshold* ranges from 5 to 30, *minimum bars apart* ranges from 51 to 266, *trades* range from 2 to 9, *winrate* ranges from 28.57% to 50.00%, *return* ranges from 50.50% to 183.71%, *max drawdown* ranges from 0.00% to -21.67%, and *profitability score* ranges from 0.6683 to 0.7707 (66.8%–77%).

1 Introduction

This paper is the fifth produced by the company and summarizes all trading model types developed so far. It is the third study in the development of the 3mTSHSUHC model, the Three-minute Timeframe Stoporder Hedging Strategy Using Heatmap Candles. Version 2 introduces a new parameter and doubles the stress test settings, making the model more complex, optimized, and refined than earlier versions. The study is fully original, with no copied ideas or external references, as the methodology was developed independently by the authors (see Appendix 1: Raw Logic and Methodology Draft). While the final model changed considerably from the original plan, the focus was on building a functional trading system rather than producing a research paper.

ChatGPT from OpenAI was used to convert the raw logic into formal mathematical formulas and code, helping to simplify and connect the ideas so that the study's goals could be achieved. This work is intended only for internal use to improve the company's trading systems and is not meant for external validation or publication.

The research focuses entirely on developing trading models for the company. Although this study mainly uses internal methods, future research should include references to strengthen the methods and support more solid conclusions. The main goal is to grow the company sustainably while following proper ethical standards.

The authors are experienced traders with knowledge of time and price patterns, volume volatility, order flow, option flow, and other aspects of the Gold Forex and Gold Futures markets. Claimed veterans but not professional enough to be certified financial advisors. Following best trading practices, they only trade with what they can afford to lose, with maintained discipline, and no emotion involved.

1.1 History of Developing the 3mTSHSUHC Trading Models

The development of the 3mTSHSUHC model, the Three-minute Timeframe Stoporder Hedging Strategy Using Heatmap Candles, has progressed through multiple studies, each refining the strategy and evaluating its performance under different conditions.

1.1.1 Birth of 3mTSHSUHC.*rp1*

The first study focused on the initial version, 3mTSHSUHC.*rp1*. With an initial balance of 1,000 units and 1% risk per trade, the model achieved a 15.22% return, a 60% win rate, a 1% maximum drawdown, and a Sharpe ratio of 8.48 across 23 intraday trades. While these results show strong short-term performance, the limited dataset and unoptimized metric-scaling reduced the strategy's consistency. The study recommended using larger datasets and refining the metric calibration to improve robustness under varying market conditions [1].

1.1.2 Stress Test of 3mTSHSUHC.*rp2*

The second study tested the same model on 500 three-minute candles using a fully automated strategy with 0.25 price unit precision and tick-volume-based decision execution scaled 0–1.

Stress parameters included a 0.30 price unit spread, 1 price unit maximum slippage, 1% commission per trade, and 5% risk per position. The study aimed to identify the Optimal Metric Threshold for trade signal execution. In ranging markets, thresholds of 0.70–0.75 produced a small number of trades (23–62) with slightly positive returns (1.4–2.3%), high win rates (38–48%), and low drawdowns (2.8–3.7%), offering the best balance of profitability, risk, and trade frequency. Low thresholds (0.00–0.20) generated excessive trades (303–312) with large losses (-49%), low win rates (8–10%), and high drawdowns (48–49%), while high thresholds above 0.80 produced very few trades (2–13) with mixed returns (-0.8% to 2.1%), win rates of 30–50%, and minimal drawdowns (1–3%), though results were statistically unreliable due to the small sample size. Overall, the study highlighted that adjusting the metric scale can improve performance and support the development of adaptive metric-scaling algorithms for varying market conditions [2].

1.2 Aim of the Study

In this study, an additional condition—*minimum bars apart*—is introduced, so a hedge signal is triggered only when both conditions are satisfied. The primary objective is to identify the optimal ranges of *metric threshold* ($y \sim 0, 0.05, \ldots, 1$) and *minimum bars apart* ($x \sim 1, 2, \ldots, 500$), evaluating 10,521 possible pairs to determine which regions generate favorable *winrate%*, *return%*, *max drawdown%*, and *profitability score* performance.

2 Methodology

2.1 Base Setup

2.1.1 Initializing MT5 and Dataset

Historical data for XAUUSD (Gold Forex) were obtained using Python through the MetaTrader 5 (MT5) platform. The dataset consists of 500 three-minute candles representing the full day of December 6, 2025. This dataset was used both for constructing analytical visualizations and for backtesting the trading model.

2.1.2 Building the Heatmap Footprint Chart

Since MT5 does not provide actual traded volumes, tick volume was used as a proxy. Individual tick volumes were distributed across their corresponding candle bars with a cluster precision of 0.25 price units. The relative volume of each candle was visually represented in a heatmap, where darker shades indicated higher tick volumes. This footprint chart provided a detailed view of market activity throughout the day.

Let T_{ij} denote the tick volume of tick j in candle i, and P_{ij} the price level of that tick. The heatmap intensity for each price cluster p in candle i is defined as:

$$H_i(p) = \sum_{j=1}^{N_i} T_{ij} \cdot \delta(p - P_{ij}) \tag{1}$$

Variable explanations: $H_i(p)$: heatmap intensity of candle i at price cluster p T_{ij}: tick volume of tick j in candle i P_{ij}: price of tick j in candle i N_i: total number of ticks in candle i $\delta(p - P_{ij})$: cluster assignment indicator

The cluster assignment function is defined as:

$$\delta(p - P_{ij}) = \begin{cases} 1, & \text{if } |p - P_{ij}| \leq 0.125 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Finally, the heatmap is normalized to scale values between 0 and 1:

$$H_i^{\text{norm}}(p) = \frac{H_i(p) - H_{\min}}{H_{\max} - H_{\min}} \tag{3}$$

Variable explanations: $H_i^{\text{norm}}(p)$: normalized heatmap intensity $H_{\min}$: minimum heatmap intensity across all candles and clusters $H_{\max}$: maximum heatmap intensity across all candles and clusters

2.1.3 Metric Scaling and Spike Detection

All tick volumes were normalized to a 0–1 scale, where 0 represented the lowest observed volume and 1 represented the highest. A *metric spike* was triggered when the normalized volume exceeded a pre-defined *metric threshold* (Y) and no previous metric spike occurred within the specified *minimum bars apart* (X). Mathematically, a metric spike occurs at candle i if:

$$S_i = \begin{cases} 1, & \text{if } H_i^{\text{norm}} > Y \text{ and } (i - i_{\text{prev}}) \geq X \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Variable explanations: S_i: spike indicator (1 if spike occurs, 0 otherwise) H_i^{norm}: normalized heatmap intensity of candle i Y: metric threshold X: minimum bars apart i_{prev}: index of previous candle where spike occurred

This study evaluated all combinations of *metric threshold* ($Y \sim 0, 0.05, \ldots, 1$) and *minimum bars apart* ($X \sim 1, 2, \ldots, 500$), resulting in 10,521 parameter pairs.

2.2 Trading Framework and Execution

Each metric spike represented a hedge signal. Upon generation of a signal, a buystop order was placed at the high of the current candle, and a sellstop order was placed at the low. The stop loss distance was fixed at three price units, while the take profit level was determined by the next signal. Each setup allowed a maximum of one unfilled entry, two filled entries, and four exits. Trades were executed only after confirmation of a signal.

Position sizing for each trade is calculated as:

$$Q_i = \frac{C \cdot R\%}{SL \cdot P_{\text{unit}}} \tag{5}$$

Variable explanations: Q_i: position size for trade i C: current capital $R\%$: risk percent per trade (5%) SL: stop loss distance in price units P_{unit}: price unit of instrument

2.3 Risk-Based Sizing and Stress Parameters

Stress parameters simulate harsh market conditions: a spread of 0.60 price units, slippage of 0–2 price units, and commission of 2% per trade. These are applied to both entries and exits. The effective entry and exit prices are calculated as:

$$P_{\text{entry, eff}} = P_{\text{entry}} + S_{\text{spread}} + S_{\text{slippage}} \tag{6}$$

$$P_{\text{exit, eff}} = P_{\text{exit}} - S_{\text{spread}} - S_{\text{slippage}} - C_{\text{comm}} \tag{7}$$

Variable explanations: $P_{\text{entry, eff}}$: effective entry price $P_{\text{exit, eff}}$: effective exit price S_{spread}: spread adjustment S_{slippage}: slippage adjustment C_{comm}: commission per trade

2.4 Single Backtesting

The Python program automated the backtesting process, including data fetching, heatmap construction, metric scaling, spike detection, trade execution, and risk application. The result was the generation of a *Raw Trades* dataset containing detailed information on every executed trade, including order type, entry and exit times, prices, stop losses, position sizes, profit and loss, exit type, and cumulative equity.

Profit and loss for each trade is calculated as:

$$\text{PnL}_i = Q_i \cdot (P_{\text{exit, eff}} - P_{\text{entry, eff}}) \tag{8}$$

Variable explanations: PnL_i: profit or loss of trade i Q_i: position size $P_{\text{exit, eff}}$: effective exit price $P_{\text{entry, eff}}$: effective entry price

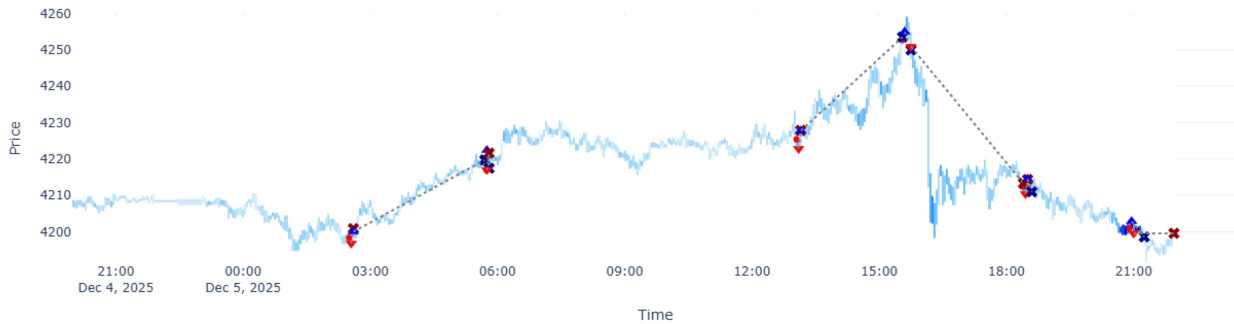

Figure 1: *Heatmap Footprint Chart and Trade Execution from the Single Backtest*

Figure 2: *Equity Curve from the Single Backtest*

What showed above is the single profile from one backtest using one pair of parameters . This result came from a prototype ready to mass produce and conduct heavy backtest using all parameters combination accounting 10521 pairs.

2.5 Trade Statistics Dataframe

Derived from the *Raw Trades* dataset, the trade statistics dataframe included the backtest run, metric threshold, minimum bars apart, number of trades, win rate, return, maximum drawdown, and a weighted scaled score (WSS).

Number of trades:

$$T(X, Y) = \sum_{i=1}^{N} S_i \tag{9}$$

Win rate:

$$W(X, Y) = \frac{\text{Number of profitable trades}}{T(X, Y)} \times 100 \tag{10}$$

Return:

$$R(X,Y) = \frac{\sum_{i=1}^{T(X,Y)} \mathrm{PnL}_i}{C_{\text{initial}}} \times 100 \tag{11}$$

Maximum drawdown:

$$D(X,Y) = \frac{\max(C_{\text{peak}} - C_{\text{trough}})}{C_{\text{initial}}} \times 100 \tag{12}$$

Weighted scaled score:

$$P(X,Y) = \frac{\text{scaled}(W(X,Y)) + \text{scaled}(R(X,Y)) + \text{scaled}(D(X,Y))}{3} \tag{13}$$

Variable explanations: $T(X,Y)$: total trades for parameter pair (X,Y) $W(X,Y)$: win rate (%) $R(X,Y)$: return (%) $D(X,Y)$: maximum drawdown (%) $P(X,Y)$: weighted scaled score (profitability score) C_{initial}: initial capital C_{peak}: peak cumulative equity C_{trough}: trough cumulative equity

2.6 Heavy Backtesting

To identify optimal parameter regions, a comprehensive heavy backtest was performed for all 10,521 possible pairs of metric threshold and minimum bars apart. Each pair was evaluated using the methodology of the single backtest, allowing the identification of regions yielding favorable win rate, return, drawdown, and profitability score.

2.7 Heavy Backtesting Dataframe

The resulting dataframe contained summary statistics for all parameter pairs. Individual raw trades were not stored in this phase to reduce computational load, as their behavior was already validated through the single-backtest dataset.

2.8 3D Chart Plotting

Interactive 3D surface plots were created using Plotly to visualize the relationship between the parameters and performance of the trading model. The y-axis represents the *metric threshold* (Y), the x-axis represents the *minimum bars apart* (X), and the z-axis represents each performance variable: total trades (T), win rate (W), return (R), maximum drawdown (D), and profitability score (P).

Each parameter pair (X,Y) produces a corresponding set of z-values calculated from the heavy backtesting:

$$T(X,Y) = \sum_{i=1}^{N} S_i \tag{14}$$

$$W(X,Y) = \frac{\sum_{i=1}^{T(X,Y)} \mathbf{1}_{\{\mathrm{PnL}_i > 0\}}}{T(X,Y)} \times 100 \tag{15}$$

$$R(X,Y) = \frac{\sum_{i=1}^{T(X,Y)} \text{PnL}_i}{C_{\text{initial}}} \times 100 \tag{16}$$

$$D(X,Y) = \frac{\max(C_{\text{peak}} - C_{\text{trough}})}{C_{\text{initial}}} \times 100 \tag{17}$$

$$P(X,Y) = \frac{\text{scaled}(W(X,Y)) + \text{scaled}(R(X,Y)) + \text{scaled}(D(X,Y))}{3} \tag{18}$$

Variable explanations: $T(X,Y)$: total number of trades generated by the parameter pair (X,Y) $W(X,Y)$: win rate in percent for the parameter pair (X,Y) $R(X,Y)$: return in percent for the parameter pair (X,Y) $D(X,Y)$: maximum drawdown in percent for the parameter pair (X,Y) $P(X,Y)$: weighted scaled profitability score for the parameter pair (X,Y) S_i: spike indicator for candle i (1 if spike occurs, 0 otherwise) PnL_i: profit or loss of trade i C_{initial}: initial capital C_{peak}: peak cumulative equity during the backtest C_{trough}: trough cumulative equity during the backtest

The 3D surface plot is constructed by mapping each (X,Y) pair to its corresponding z-value (T,W,R,D,P). The visualization allows for the identification of parameter regions that maximize profitability while controlling risk. Each surface is interpolated across all 10,521 parameter pairs to provide a smooth representation of performance metrics. This graphical approach facilitates clear identification of operationally optimal areas in the parameter space for strategy deployment.

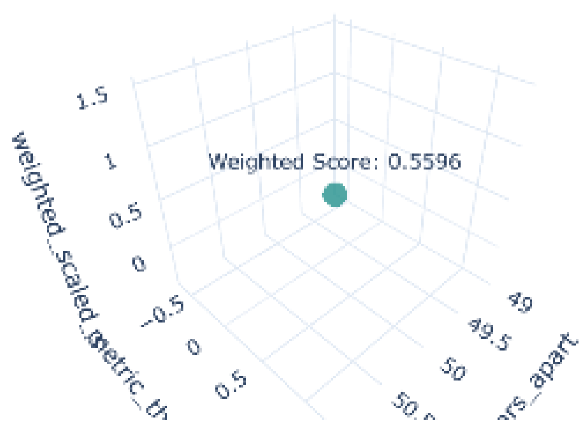

Figure 3: *3D plotting example, using x-bars apart, y-metric treshold, and z-profitability score*

What shown above is the example of the plotted value of z-variable corresponding to the xy-variables. Its the prototype for using 1 out of 10521 xy pairs. This was set for mass production during the heavy backtesting phase.

3. Results and Findings

3.1 Trades

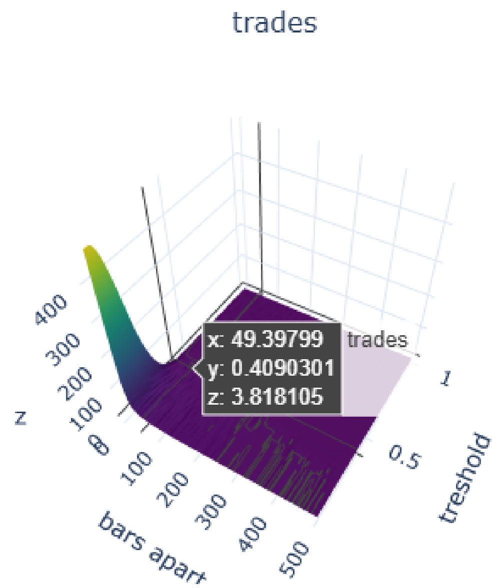

Figure 4: *The y-threshold, x-barsapart, and z-trade correlation*

The findings show that to achieve higher *trades* results, the *metric threshold* must be set and limited approximately around 40, and the *minimum bars apart* is approximately around 50.

3.2 Winrate

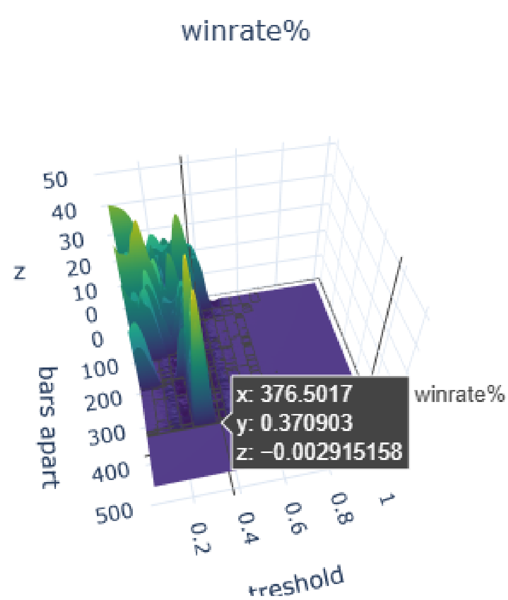

Figure 5: *The y-threshold, x-barsapart, and z-winrate correlation*

The findings show that to achieve higher *winrate*, the *metric threshold* must be set and limited approximately around 37, and the *minimum bars apart* is approximately around 377.

3.3 Return

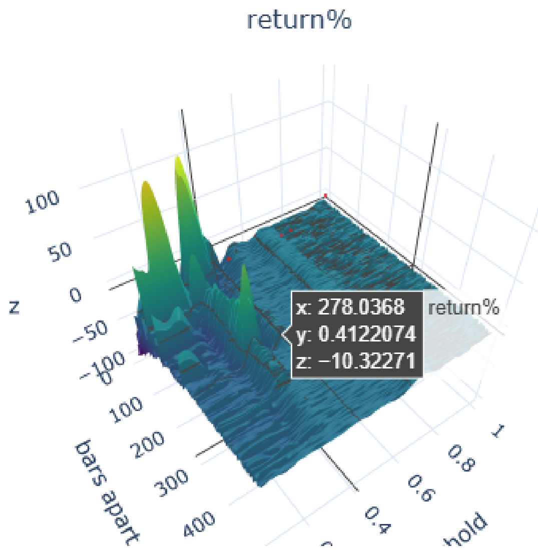

Figure 6: *The y-threshold, x-barsapart, and z-return correlation*

The findings show that to achieve higher *return*, the *metric threshold* must be set and limited approximately around 41, and the *minimum bars apart* is approximately around 278.

3.4 Drawdown

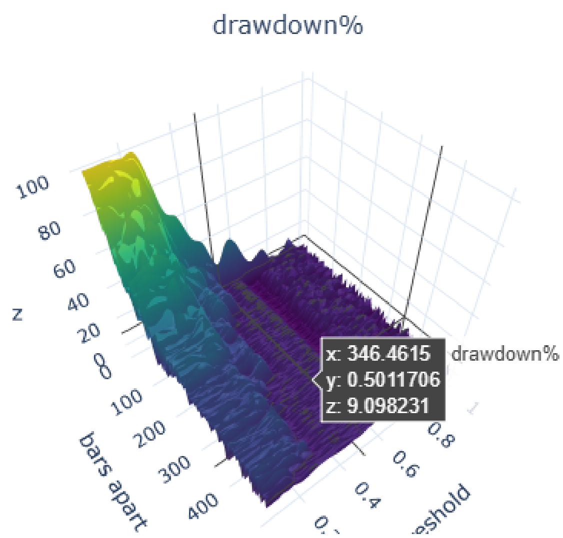

Figure 7: *The y-threshold, x-barsapart, and z-drawdown correlation*

The findings show that to achieve higher *drawdown*, the *metric threshold* must be set and limited approximately around 50, and the *minimum bars apart* is approximately around 346.

3.5 Winrate vs Drawdown

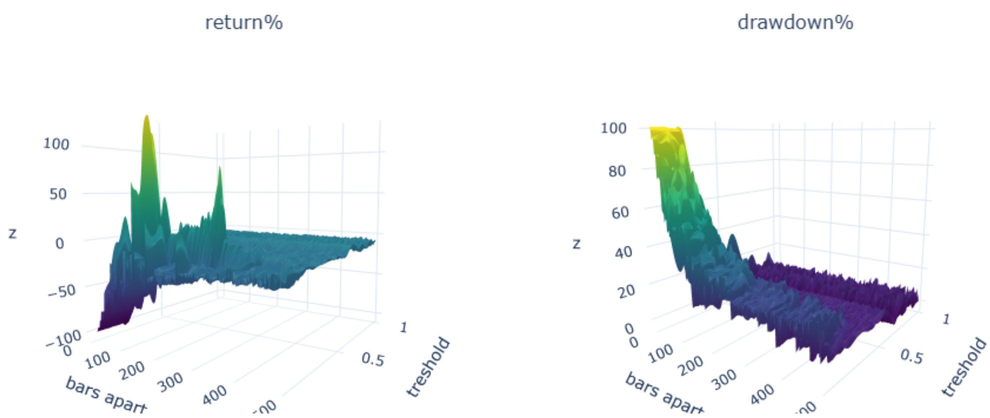

Figure 8: *The return and drawdown correlation*

The findings show that *winrate* and *drawdown* start inversely correlated before the *metric threshold* is approximately around 45, and the *minimum bars apart* starts approximately around 300.

3.6 Profitability Score

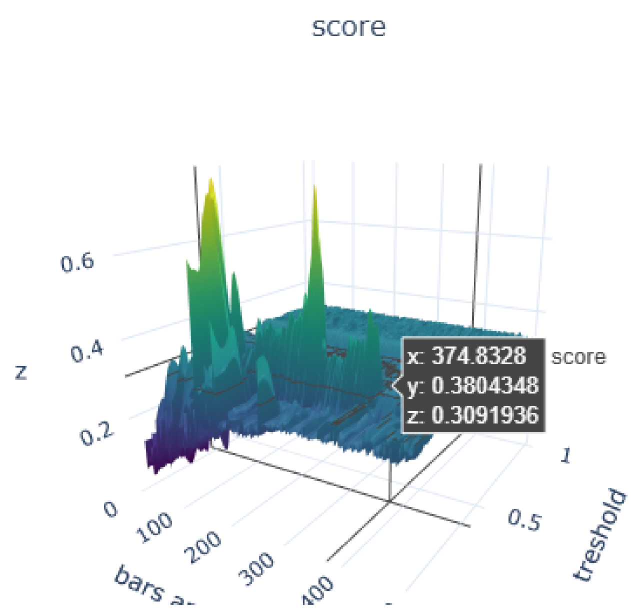

Figure 9: *The y-threshold, x-barsapart, and z-profitability score correlation*

The findings show that to achieve higher *profitability score*, the *metric threshold* must be set and limited approximately around 38, and the *minimum bars apart* is approximately around 375.

3.7 Minimum and Maximum Values of Z-variables

	metric	min_value	max_value
0	num_trades	1.000	477.0000
1	winrate_pct	0.000	50.0000
2	return_pct	-100.200	169.7900
3	max_drawdown_pct	0.000	100.7900
4	weighted_scaled_s	0.035	0.7646

Figure 10: *Minimum and maximum values of z-variables*

The findings indicate that, for the given x–y combinations of *metric threshold* and *minimum bars apart*, the corresponding z-variable values exhibit the following ranges: Minimum *trades* of 1 and a maximum of 477. Minimum *winrate* of 0 and a maximum of 50. Minimum *return* of -100.20 and a maximum of 169.79. Minimum *drawdown* of 0 and a maximum of 100.79. Minimum *profitability score* of 0.035 and a maximum of 0.76. This results came from a single compiled code, covering all 5 graphs.

3.8 Performance Score Region

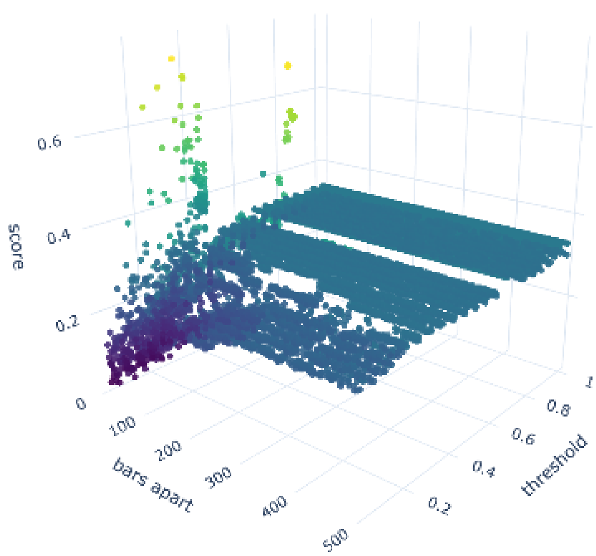

Figure 11: *Performance Score of 10521 possible pairs*

The findings indicate that in order to get favorable results, at approximately a *metric threshold* (y) of 40 and a *minimum bars apart* (x) of approximately 320, as this region consistently demonstrates a drastic change in difference of possible outcome in terms of *winrate*, *return*, and *drawdown*, which is used by the formula for *profitability score* performance.

3.9 Top 10 Parameter Combinations

```
TOP 10 PARAMETER COMBINATIONS BY SCORE:

      metric_threshold  min_bars_apart  num_trades  winrate_pct  return_pct  \
1123              0.15             124           7        42.86      183.71
2762              0.30             263           2        50.00       79.41
2761              0.30             262           2        50.00       78.42
622               0.10             123           6        33.33       97.18
2550              0.30              51           9        33.33      106.41
2551              0.30              52           9        33.33      105.83
122               0.05             123           7        28.57       89.57
2764              0.30             265           2        50.00       52.80
2763              0.30             264           2        50.00       52.21
2765              0.30             266           2        50.00       50.50

      max_drawdown_pct  weighted_scaled_s
1123             11.65             0.7707
2762              0.00             0.7647
2761              0.00             0.7614
622              14.74             0.7193
2550             20.22             0.7104
2551             21.67             0.7055
122              12.33             0.6860
2764              0.00             0.6760
2763              0.00             0.6740
2765              0.00             0.6683
```

Figure 12: *Top 10 Parameter Combination by profitability score*

The findings indicate that, in order to achieve a favorable *profitability score*, the region where the *metric threshold* values range from a minimum of 5 to a maximum of 30, and where the *minimum bars apart* parameter spans from 51 to 266 bars, is where the top 10 *profitability score* performances reside. The number of *trades* varies between a low of 2 and a high of 9. *Winrate* ranges from 28.57 to 50.00. *Return* fluctuates from 50.50 to 183.71. Maximum *drawdown* ranges from 0.00 to -21.67, and *profitability score* ranges from 0.6683 to 0.7707 (66.8 to 77).

This result was obtained from a separate compiled code that focuses solely on the *profitability score* performance. Statistical values changed due to applied stress parameters, demonstrating that the 3mTSHSUHC.*rp3* model remains capable of achieving top scores within the discussed region.

4. Conclusion

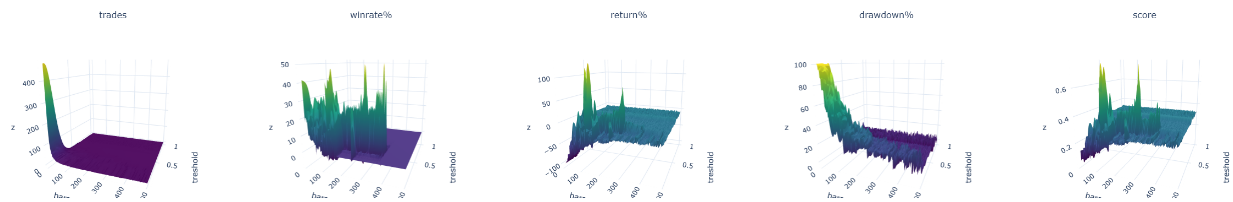

Figure 13: *The x-bars apart, y-metric threshold, and respective z-variables: trades, winrate, return, drawdown, and profitability score performance*

4.1 Interaction Between Parameters

The results collectively demonstrate that the interaction between the *metric threshold* (y) and the *minimum bars apart* (x) plays a decisive role in shaping all major performance variables, including *trades*, *winrate*, *return*, *drawdown*, and the overall *profitability score*. Across all tested parameter combinations, performance behavior is clearly non-linear, with distinct regions of degradation and optimization emerging consistently across multiple statistical dimensions.

4.2 Optimal Operational Region

From the aggregated surface plots and optimized score distributions, the most stable and favorable operational region is concentrated around a *metric threshold* of approximately 40 and a *minimum bars apart* near 320 bars. This region exhibits a balanced convergence of elevated *return*, controlled *drawdown*, moderate-to-high *winrate*, and a consistently strong *profitability score*. Outside of this region, performance deteriorates either through excessive *drawdown* at higher thresholds or insufficient opportunity generation and poorer *return* at lower thresholds.

4.3 Trade-offs Between Objectives

While individual optimizations differ by objective, such as maximizing *winrate* near ($y \approx 37, x \approx 377$) or maximizing *return* near ($y \approx 41, x \approx 278$), these isolated optima introduce undesirable trade-offs when evaluated holistically. Higher *winrate* regions tend to suppress *return* due to reduced *trades*, whereas higher *return* regions often coincide with elevated *drawdown*. The *profitability score* surface effectively integrates these competing dynamics and confirms that extreme parameter values are structurally inefficient for sustained performance.

4.4 Validation via Top 10 Combinations

The Top 10 parameter combinations further validate this conclusion by clustering within low-to-mid *metric threshold* values and moderate *minimum bars apart*. Despite variations introduced by stress parameters in the recompilation process, the *profitability score* remains structurally bounded within the same region, confirming the robustness of the model's performance landscape. The observed consistency across both single-run and stressed simulations reinforces the stability of the identified optimal zone.

4.5 Summary

In summary, the findings indicate that neither aggressive sensitivity (low x, low y) nor excessive filtering (high x, high y) is optimal. Instead, a controlled middle regime centered near ($y \approx 40, x \approx 320$) provides the most reliable balance between opportunity frequency, risk containment, and *return* efficiency. This region represents the practical operating envelope for deploying the model under realistic trading constraints and offers a statistically defensible foundation for future model tuning, live deployment, and extended Monte Carlo validation.

4.6 Concluding Statement

This study aimed to identify the optimal range of *metric threshold* ($y \sim 0, 0.05, \ldots, 1$) and *minimum bars apart* ($x \sim 1, 2, \ldots, 500$), accounting for 10,521 possible pairs, to found out which regions generates favorable *winrate%*, *return%*, *max drawdown%*, and *profitability score* performance. By restricting the *metric threshold* and *minimum bars apart* near ($y \approx 40, x \approx 320$), 4,160 possible pairs fall within this optimal zone, representing a 60.5% improvement over using all combinations. Within this region, the top 10 performing pairs were identified, where *metric threshold* ranges from 5 to 30, *minimum bars apart* ranges from 51 to 266, *trades* range from 2 to 9, *winrate* ranges from 28.57% to 50.00%, *return* ranges from 50.50% to 183.71%, *max drawdown* ranges from 0.00% to -21.67%, and *profitability score* ranges from 0.6683 to 0.7707 (66.8%–77%).

References

[1] Albeos, Rembrant. (2025, December 6). *The 3mTSHSUHC.rp1: Design and Optimization of Three-minute Timeframe Stoporder Hedging Strategy Using Heatmap Candles.* GitHub.
https://github.com/algorembrant/QAT-QuantitativeAlgorithmicTrading/tree/main/Research%20Papers/The%203mTSHSUHC.rp1%3A%20Design%20and%20Optimization%20of%20Three-minute%20Timeframe%20Stoporder%20Hedging%20Strategy%20Using%20Heatmap%20Candles%20

[2] Albeos, Rembrant. (2025, December 6). *The 3mTSHSUHC.rp2: Stress Test & Evaluating the Three-minute Timeframe Stoporder Hedging Strategy Using Heatmap Candles.* GitHub.
https://github.com/algorembrant/QAT-QuantitativeAlgorithmicTrading/tree/main/Research%20Papers/The%203mTSHSUHC.rp2%3A%20Stress%20Test%20%26%20Evaluating%20the%20Three-minute%20Timeframe%20Stoporder%20Hedging%20Strategy%20Using%20Heatmap%20Candles%20

Appendix: Raw Logic and Methodology Draft

This study utilizes Python for programming and MT5 communication to fetch XAUUSDc data. The development process involved conceptualizing the logic, formulating mathematical representations, explaining all variables and mechanics, coding the model, plotting results, and drawing conclusions.

.1 Setting the Heatmap Candle Chart

1. Data set: 500 3-minute timeframe candles, from the current time to 500 previous candles.
2. Current candle: cu
3. Heatmap candles: tick-volume bars distributed on candlesticks with 0.25 price unit cluster precision.
4. Heatmap candle HCu: individual heatmap candle.
5. Tick-volume scale: range from lowest to highest raw tick-volume across all 500 candles.

.2 Trade Hedge Signal Logic

1. Metric scale: optimized scale for tick-volume, normalized between 0 and 1.
2. Metric threshold: condition for metric spike signal. For example, if $TV_{cu} > 0.60$, the condition is met. This study considers thresholds from 0.60 to 1.00 in increments of 0.05.
3. Metric Spike version 1: occurs when the metric threshold condition is met.
4. Numlook: number of lookback heatmap candles (e.g., 50).
5. Numlook Check: ensures no Metric Spike version 1 exists within the lookback window. This study uses 1 to 500.
6. Metric Spike version 2: occurs when both Metric Threshold and Numlook Check are satisfied, generating a hedge signal.

.3 Trade Positioning Logic

1. Hedge signal placement: upon Metric Spike version 2, place a buy stop at the body-high of HC_{cu} and a sell stop at the body-low, with a 3 price unit stop-loss (SL), risking 5% per trade.
2. Take profit (TP): varies, set at the next hedge signal.
3. Risk management: 5% of latest balance per trade using 3 price unit SL.
4. Initial equity: 1000 balance units.

.4 Trading Model Training Logic

1. Data set: 500 3-minute heatmap candles.
2. Stress parameters:
    - Slippage: 2.0 price units
    - Spread: 0.60 price units
    - Commission: 2% per entry and exit
3. Stress test: simulated backtesting combining Trade Hedge Signal Logic, Trade Positioning Logic, Risk Management, and Stress Parameters.
4. PnL Values: derived from stress test results.
5. Equity curve: cumulative PnL values over time, limited to the dataset.
6. Final Equity Profile: end value of the equity curve, including win rate, return, and drawdown percentages.
7. Monte Carlo Simulation: 100 runs per parameter pair to generate multiple equity curves and final equity profiles.
8. Weighted Final Equity Profile: weighted mean of the 100 Monte Carlo runs.
9. Scaled Profitability Score (SPS): scaled mean of the weighted final equity profile, normalized from 0 (lowest) to 1 (highest):

$$SPS = \frac{\text{scaled Weighted Final Equity Profile}}{3}$$

.5 Study Objective

To determine the best-performing pair of parameters: one from Metric Threshold (0.60, 0.65, ..., 1.00) and one from Numlook Check (1, 2, ..., 500) that maximizes the Scaled Profitability Score. Total possible parameter pairs: $9 \times 500 = 4500$.

.6 Plotting and Visualization

1. 3D Graph:
    - y-axis: Metric Threshold values
    - x-axis: Numlook Check values
    - z-axis: Scaled Profitability Score
2. Each bubble represents the SPS from one pair of parameters over 100 Monte Carlo runs, totaling 450,000 bubbles.
3. Bubbles are colored using K-means clustering; darker colors indicate SPS closer to 1. K-means++ is used for optimization.