Quantitative Market Structure Model (QMSM)

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Overview

This project implements a bias-aware, event-driven trading system designed to operate under near-live market conditions. The system focuses on eliminating look-ahead bias, controlling execution latency, and enforcing explicit risk constraints while remaining deployable in real trading environments.

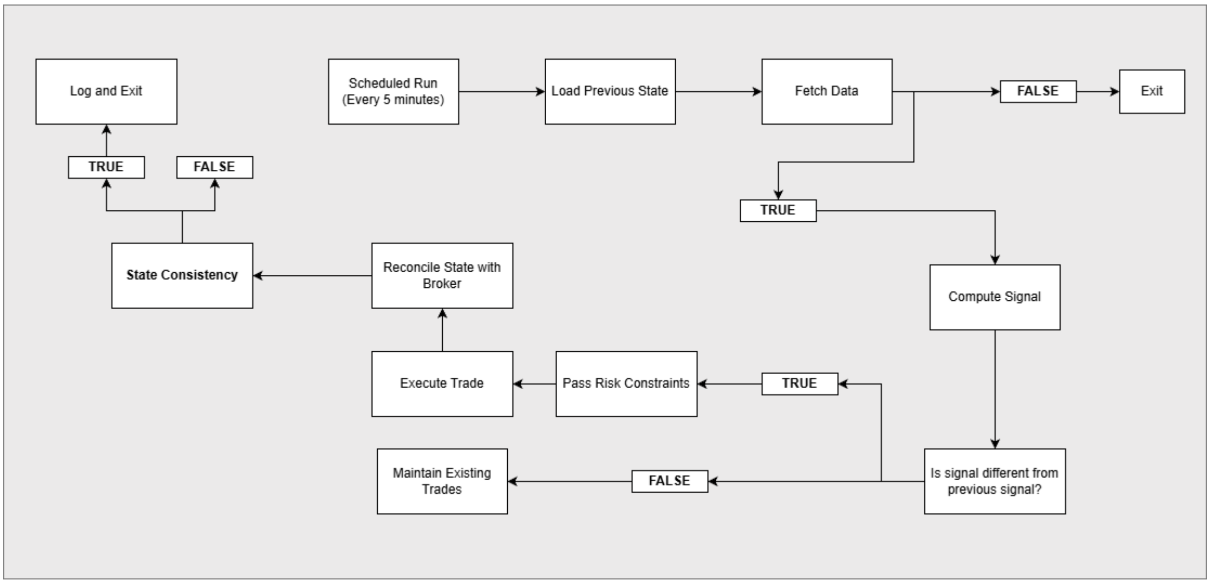

Figure 1: Execution & Safety Flow.

Scope & Intent

This document is intended as a technical summary of the design, implementation, and execution logic of the Quantitative Market Structure Model (QMSM). The purpose of this write-up is not to empirically prove the existence of a persistent trading edge or to validate a statistical hypothesis, but rather to formalise the system architecture, signal construction principles, and risk controls underpinning a live-deployable trading model. Backtest results are therefore presented for diagnostic and illustrative purposes only, and should not be interpreted as evidence of statistical optimality or long-term performance guarantees.

Signal Design

An earlier version of the algorithm used conventional peak-detection methods, such as scipy.signal.find_peaks, to identify swing highs and lows. While this approach appeared effective, its apparent success was largely driven by forward-looking bias. In particular, a price had to move away from a local extremum before it could be classified as a peak or trough, meaning that confirmation was only possible after the move had already occurred. This delayed recognition introduced execution latency, leading to systematically late trade entries and a consequent loss of signal alpha.

To combat this, we require a first layer detection logic capable of reducing latency all the while maintaining to some extent the winning properties of previous peak-finding methods. That being said, our makeshift detection logic must be capable of;

- Signal detection with a minimum latency of one bar.
- Trading expectancy is sacrificed in exchange for faster execution and a higher probability of entry accuracy.
- Independence from price structure to eliminate look-ahead bias.

0.1 Assessing Individual Bars

For signal detection to remain free of look-ahead bias and to operate at minimal latency, the detection logic must be constructed from information available within a single completed bar, rather than from multi-bar price formations. Any method that relies on identifying swings, trends, or structural extrema necessarily requires future price evolution and therefore introduces forward-looking bias.

Each OHLC bar is therefore represented as a one-dimensional price vector over the sampling interval. Let a bar be defined by its open O, high H, low L, and close C as in eq(1). The bar's effective price displacement can be interpreted as the magnitude of this vector, which quantifies the total directional and intrabar movement realized during that interval. This scalar quantity provides a structure-free measure of price activity that is fully observable at the close of the bar. To further standardise this quantity, the magnitude is normalised by the closing price, producing a dimensionless measure that reflects price expansion or contraction relative to the prevailing level, as in eq(2).

Let a completed OHLC bar be represented as

$$\mathbf{x}_t = \begin{bmatrix} O_t & H_t & L_t & C_t \end{bmatrix}. \tag{1}$$

The bar-level magnitude is defined as

$$M_t = \frac{\mathcal{M}(\mathbf{x}_t)}{C_t}, \tag{2}$$

where $\mathcal{M}(\cdot)$ denotes a scalar magnitude operator acting on the OHLC vector.

Figure 2 illustrates this magnitude-based representation alongside real GBPUSD price action, showing how peaks and troughs are detected directly from bar-level displacement rather than from multi-bar pattern formation.

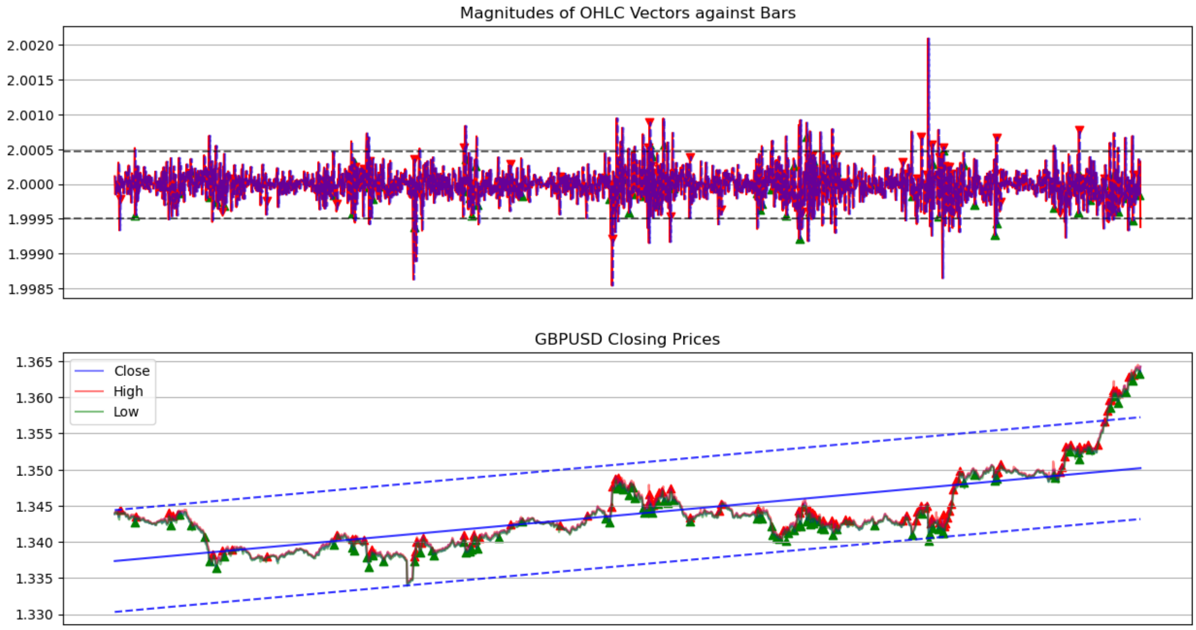

Figure 2: **GBPUSD** - Peaks and Troughs detected through Magnitude Vector logic overlayed on real closing prices.

By operating on this bar-level magnitude rather than on multi-bar extrema, the model produces signals that are immediately available at the end of each bar, ensuring minimal detection latency and eliminating any dependence on future price information.

To contextualise these bar-level movements, price is additionally modelled relative to a rolling linear regression mean and associated standard-deviation bands. These are estimated over a specified bar window, providing a dynamically updated reference frame that normalises each bar's magnitude by prevailing market conditions. This allows the system to distinguish statistically significant displacements from routine noise, while remaining anchored to short-to-medium-term volatility rather than long-horizon trend structure.

0.2 Signal Generation

Buy and sell signals are generated when a statistically significant peak or trough is detected within predefined overbought or oversold regions using the Magnitude Vector framework.

The overbought and oversold regions are defined relative to the rolling linear-regression mean and its associated standard-deviation bands as follows:

- Overbought (Short Zone) - Price lies between the upper σ band and the midpoint between the upper σ band.
- Oversold (Long Zone) - Price lies between the lower σ band and the midpoint between the lower σ band.

The performance of this strategy is evaluated through multi-year backtesting across multiple financial instruments, ensuring that results are not specific to a single market or regime.

The combined use of the Magnitude Vector framework and regression-based volatility bands is deliberately chosen to minimise signal latency and reduce reliance on higher-level market structure. In designing the system, care was taken to avoid conventional threshold-based indicators—such as RSI—which can introduce leakage and overfitting due to their dependence on fixed absolute levels. Instead, the strategy relies exclusively on mechanically defined, scale-invariant rules derived directly from price dynamics.

Backtesting Framework

To faithfully replicate live trading conditions, the backtest is executed sequentially on a bar-by-bar basis rather than by slicing the dataset into fixed windows. Since regression bands and associated state variables are recomputed for each incoming bar, all trade parameters—including entry, stop-loss, and take-profit levels—are recalculated dynamically at each step.

Trade outcomes are resolved by iterating forward through subsequent bars to determine whether take-profit or stop-loss levels are reached first, ensuring an unbiased and mechanically consistent evaluation of each trade.

The backtesting engine assumes execution exclusively via market orders, reflecting the intended live deployment model and avoiding assumptions related to limit or stop-order fill quality. As all signal logic is derived solely from contemporaneously available bar-level information, the framework is free from data leakage and look-ahead bias by construction.

Finally, signal detection latency is explicitly quantified, with the system designed to target a maximum latency of one bar between signal generation and execution.

Backtest is performed bar-by-bar from the year 2018 until 2025. Data is downloaded from dukascopy.

0.3 Assumptions

- Bid–ask spread is assumed to be zero in the backtesting environment. To partially account for transaction costs, the reported risk–reward (R:R) is conservatively adjusted by a fixed deficit of $-0.2R$, representing the combined impact of spread, swaps, and execution friction.
- Stop-loss (SL) and take-profit (TP) levels are not explicitly spread-adjusted. In live deployment, effective TP levels would be marginally reduced and SL levels marginally increased for long positions (and vice versa for short positions) due to execution at bid–ask prices.
- Trades are executed irrespective of scheduled macroeconomic or news events occurring on the relevant trading day.

In computing metrics such as drawdown behaviour, net R from the trades entered in the backtest are computed cumulatively.

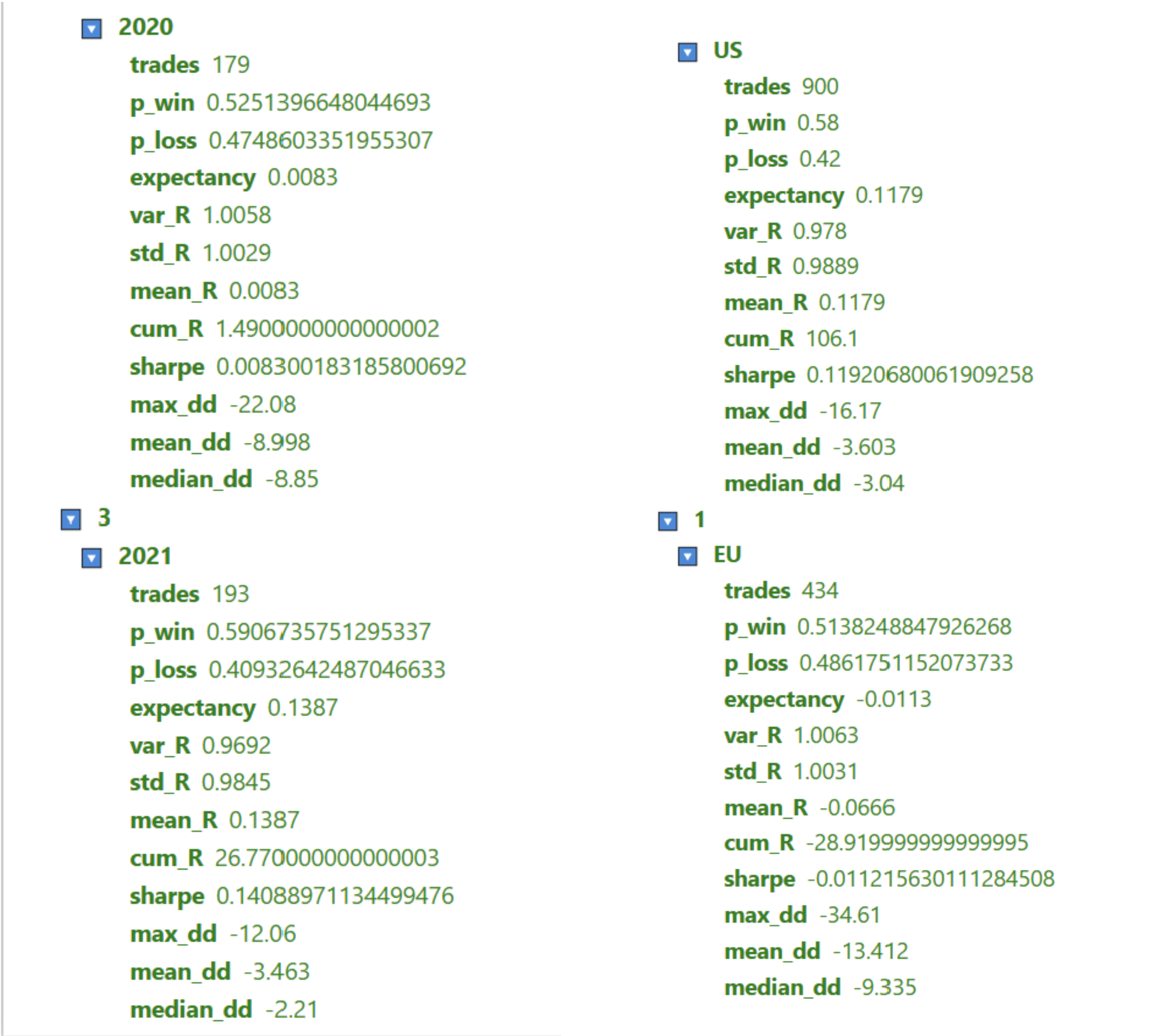

Figure 3: [L] Backtest Results for GBPUSD per year [R] Backtest Results for USDCAD per session. Both forms of data are saved in the form of JSON.

Asset Class of Instruments

To construct a robust multi-instrument trading system, instruments are selected across asset classes that exhibit complementary risk and return characteristics. In particular, preference is given to instruments demonstrating positive expectancy, controlled drawdowns, and favourable risk-adjusted performance metrics.

To evaluate cross-asset robustness, the strategy was independently tested across multiple asset classes, including foreign exchange pairs, equity indices, and commodities. This assessment is intended to verify that performance is not isolated to a single market structure or regime, but instead generalises across instruments with differing volatility profiles, liquidity conditions, and trading dynamics.

	trades	p_win	p_loss	expectancy	var_R	std_R	mean_R	cum_R	sharpe	max_dd	mean_dd	median_dd	calmar_ratio
SNP	1282	0.614665	0.385335	0.1840	0.9392	0.9691	0.1840	235.84	0.189827	-18.40	-2.820	-2.000	1.602174
GBPUSD	1478	0.608931	0.391069	0.1765	0.9537	0.9766	0.1765	260.88	0.180741	-23.92	-3.717	-2.265	1.363294
EURUSD	1447	0.591569	0.408431	0.1409	0.9719	0.9859	0.1409	203.88	0.142917	-22.44	-4.805	-3.360	1.135695
USDCAD_US	900	0.580000	0.420000	0.1179	0.9780	0.9889	0.1179	106.10	0.119207	-16.17	-3.603	-3.040	0.820192
USDCAD	1597	0.551659	0.448341	0.0607	0.9934	0.9967	0.0607	96.86	0.060854	-29.41	-7.150	-6.110	0.411680
AUDUSD	1730	0.549711	0.450289	0.0549	0.9985	0.9993	0.0549	95.02	0.054965	-38.79	-7.548	-5.165	0.306200
DAX	1316	0.532675	0.467325	0.0232	0.9931	0.9965	0.0232	30.57	0.023311	-39.68	-10.529	-8.415	0.096302
GBPJPY	1504	0.532580	0.467420	0.0211	1.0053	1.0026	0.0211	31.80	0.021088	-50.26	-19.671	-16.805	0.079089
US30.cash	1398	0.533619	0.466381	0.0206	0.9945	0.9973	0.0206	28.75	0.020622	-32.80	-11.918	-11.620	0.109566
USDCHF	1541	0.530175	0.469825	0.0157	1.0139	1.0069	0.0157	24.13	0.015551	-64.74	-22.409	-18.680	0.046590
XAUUSD	1293	0.529776	0.470224	0.0146	0.9991	0.9996	0.0146	18.85	0.014585	-57.90	-24.561	-25.560	0.040695
EURJPY	1453	0.506538	0.493462	-0.0297	1.0002	1.0001	-0.0297	-43.16	-0.029701	-96.55	-53.592	-53.920	-0.055878

Figure 4: Backtest performed across multiple instruments across different assets.

Figure 4 summarises the backtest results across the tested instruments, reporting key performance and risk metrics for each. The results highlight meaningful variation in expectancy and drawdown behaviour across asset classes, reinforcing the importance of portfolio-level instrument selection rather than reliance on any single market.

Reported results reflect instrument-level diagnostics rather than the final portfolio configuration used in live deployment.

Risk Profile of Chosen Assets

Based on the backtest results presented in Figure 3, it is evident that the trading logic exhibits stronger performance in certain asset classes and, more specifically, in a subset of instruments. Given the range of performance and risk metrics computed for each backtest, an ideal candidate instrument is characterised by the following properties:

- Consistently positive and stable expectancy over the full backtest horizon.
- Favourable risk-adjusted performance, as reflected by high Sharpe and Calmar ratios.
- Controlled drawdown behaviour, characterised by a low maximum drawdown and reasonable mean and median drawdowns.

	trades	p_win	p_loss	expectancy	var_R	std_R	mean_R	cum_R	sharpe	max_dd	mean_dd	median_dd	calmar_ratio
SNP	1282	0.614665	0.385335	0.1840	0.9392	0.9691	0.1840	235.84	0.189827	-18.40	-2.820	-2.000	1.602174
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Figure 5: Backtest results sorted by expectancy and Calmar ratio.

From the ranked results shown in Figure 4, equity indices—most notably the S&P 500—exhibit the highest expectancy while maintaining comparatively low maximum drawdowns relative to the cross-instrument average (mean maximum drawdown of -40.91R). This is followed by major FX instruments including GBPUSD, EURUSD, and USDCAD, which demonstrate similarly favourable trade-offs between expectancy and drawdown control.

These results are consistent with the underlying design of the algorithm, which is inherently responsive to trending market conditions and sensitive to periods of accelerated price movement driven by momentum. Instruments exhibiting sustained directional behaviour and episodic volatility expansion are therefore more naturally aligned with the model's detection logic.

The backtests span the period from 2018 to 2025, explicitly including the market disruptions associated with the COVID-19 pandemic during 2020 and 2021. While such periods are frequently excluded as outliers in conventional backtesting studies, they are intentionally retained here to evaluate how the system behaves under extreme market stress as well as black swan events. This provides a more realistic assessment of robustness and drawdown dynamics during low-probability, high-impact events, rather than optimising performance solely for benign market regimes.

0.4 Portfolio Construction - Correlation Study

As established in the previous section, only four instruments exhibited an expectancy exceeding 0.1 over the backtest horizon: EURUSD, GBPUSD, the S&P 500, and USDCAD during the US trading session. The next step is therefore to construct a portfolio from this subset of candidate instruments.

However, portfolio formation requires consideration beyond standalone instrument performance. In particular, inter-instrument correlation must be examined to ensure that aggregate portfolio risk is not inadvertently amplified. For instance, although both GBPUSD and EURUSD demonstrate favourable expectancies individually, trading them concurrently effectively constitutes an increased directional exposure to the quoted currency, USD. While such exposure may be acceptable if cumulative returns sufficiently outweigh combined drawdowns, it introduces concentration risk that can materially increase portfolio-level drawdown.

The objective is therefore to assemble a portfolio composed of instruments whose return streams exhibit low or negative correlation, thereby improving drawdown characteristics without materially sacrificing expectancy. Although a portfolio consisting solely of highly correlated instruments such as GBPUSD and EURUSD may yield higher nominal returns in backtests, it is also likely to experience deeper and more prolonged drawdowns.

To evaluate these interactions, a correlation analysis across the shortlisted instruments though historical daily returns is presented below in Figure 6.

Correlation coefficients are derived through Numpy's **np.corrcoeff function**.

	EURUSD	GBPUSD	SNP500	USDCAD
EURUSD	1.000000	0.646083	-0.020962	-0.511734
GBPUSD	0.646083	1.000000	0.016429	-0.504119
SNP500	-0.020962	0.016429	1.000000	-0.032294
USDCAD	-0.511734	-0.504119	-0.032294	1.000000

Figure 6: Correlation Study between EURUSD, GBPUSD, S&P 500 and USDCAD.

In Figure 5, GBPUSD and EURUSD exhibit a strong positive correlation, with a correlation coefficient of 0.646, indicating a high tendency for both instruments to move in the same direction. This behaviour is consistent with their shared exposure to the USD and similar macroeconomic drivers.

In contrast, when GBPUSD and EURUSD are paired with other instruments, the correlation structure changes materially. Both currency pairs display a negative correlation with USDCAD, while their correlation with the S&P 500 is effectively negligible. Specifically, the EURUSD–S&P 500 correlation is -0.002, and the GBPUSD– S&P 500 correlation is 0.016, indicating near independence between these instruments.

Given that GBPUSD and EURUSD also exhibit the highest individual expectancies among the shortlisted instruments, particular emphasis is placed on their role within the portfolio. However, due to their strong mutual correlation, including both simultaneously would increase concentration risk and amplify portfolio drawdowns during adverse periods.

A more balanced portfolio configuration therefore considers the S&P 500 as the primary return driver, supplemented by either GBPUSD or EURUSD as a secondary contributor, with USDCAD included to provide a partial hedge against currency-driven drawdowns due to its negative correlation with both EURUSD and GBPUSD.

Based on this analysis, two candidate portfolio configurations are considered:

Portfolio	Primary Return	Secondary Contributor	Hedge
Portfolio 1	S&P 500	GBPUSD	USDCAD
Portfolio 2	S&P 500	EURUSD	USDCAD

Table 1: Portfolio Configurations

The best portfolio would be defined by the portfolio with the highest expectancies, lowest max/mean/median drawdowns all the while having a high calmar ratio.

Figure 7 represents the drawdown profile for each portfolio throughout the backtesting period of 2018-2025.

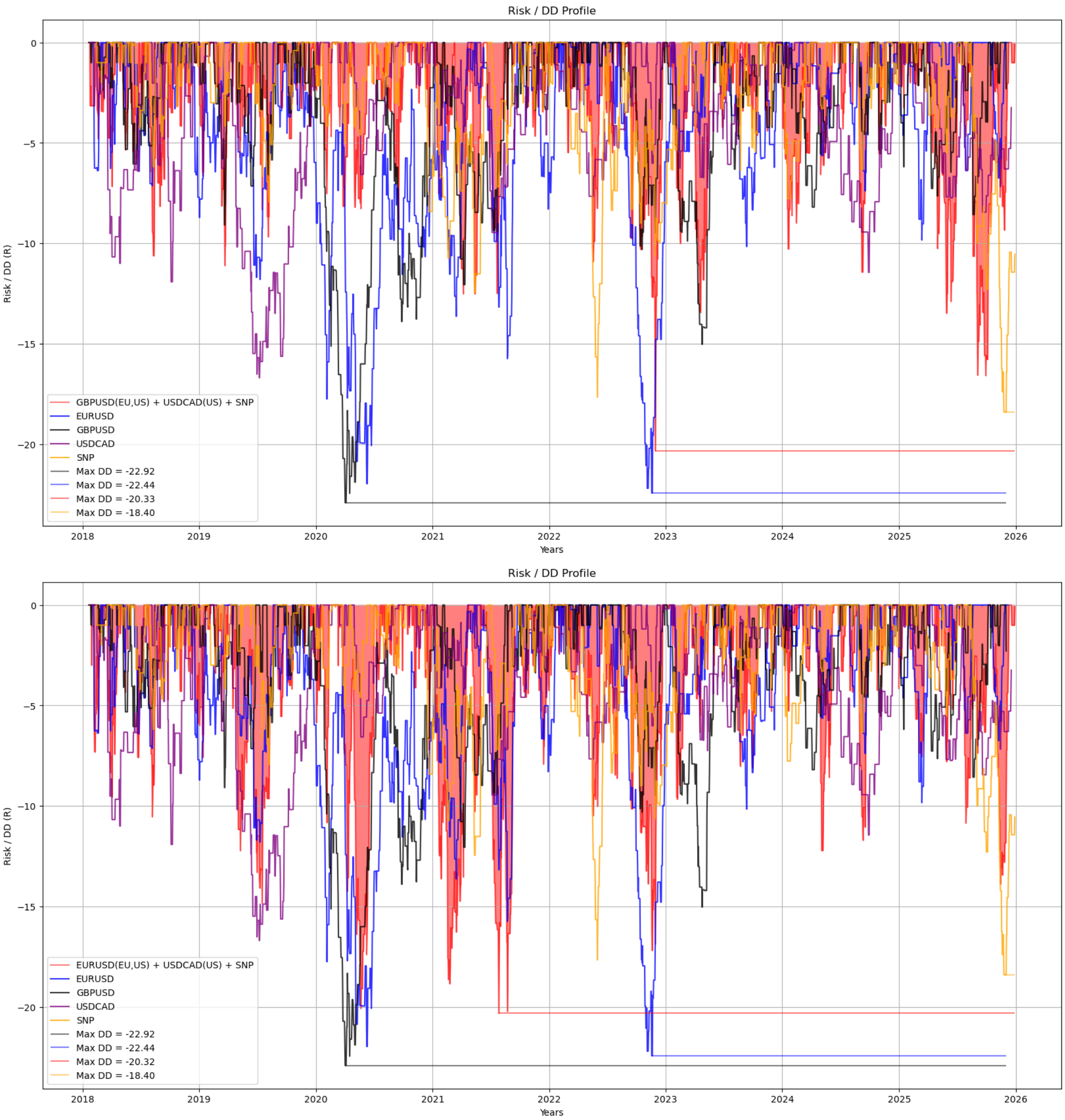

Figure 7: [Top] - Portfolio 1 Drawdown. [Bottom] - Portfolio 2 Drawdown.

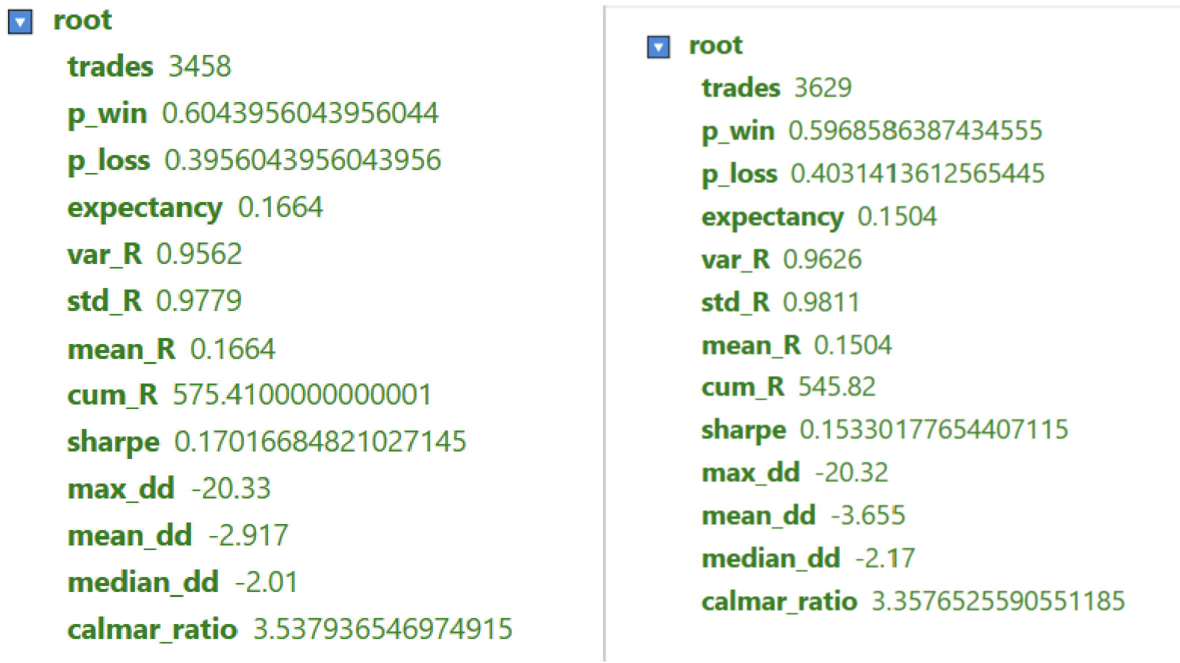

Figure 8: Portfolio Metrics for [L] Portfolio 1 & [R] Portfolio 2.

0.5 Portfolio Summary

As shown in Figure 8, both portfolio configurations experienced comparable maximum drawdowns over the 2018–2025 backtest horizon, at approximately -20.3 R. However, these drawdowns did not occur during the same periods. As illustrated in Figure 7, Portfolio 1 reached its maximum drawdown toward the end of 2022, whereas Portfolio 2 experienced its maximum drawdown earlier, around mid-2021.

Notably, during the COVID-19 period - a low-probability, high-impact "black swan" event - Portfolio 1 exhibited substantially greater drawdown resilience than Portfolio 2. Portfolio 1 sustained a drawdown of approximately -8 R, while Portfolio 2 experienced a significantly deeper drawdown of around -20 R over the same period. This observation suggests that Portfolio 2 is more vulnerable to global shocks and periods of systemic stress. The inclusion of USDCAD in Portfolio 1 appears to provide a more effective hedging effect, helping to contain drawdowns during extreme market conditions.

This difference in risk behaviour is further reflected in the distributional statistics shown in Figure 8. Portfolio 1 exhibits lower median and mean drawdowns (-2.01 R and -2.92 R, respectively) compared to Portfolio 2 (-2.17 R and -3.66 R). In addition, Portfolio 1 demonstrates higher expectancy, more stable Sharpe and Calmar ratios, and lower variance in R per trade relative to Portfolio 2.

Overall, considering both tail-risk behaviour and central drawdown tendencies, **Portfolio 1 is preferred**. It achieves superior drawdown control while maintaining favourable expectancy and risk-adjusted performance, indicating a more robust balance between return generation and risk containment across varying market regimes.

Algorithm Process Flow and Pipeline

This section describes the end-to-end execution pipeline of the Quantitative Market Structure Model (QMSM) algorithm, outlining how individual system components interact to produce signals, manage state, and execute trades under live trading conditions. Rather than detailing individual functions in isolation, the focus here is on the control flow, data dependencies, and state transitions that govern the algorithm's operation.

File / Component	**Primary Responsibility**
`main_skeleton.ipynb`	Computes market state and structural events required for signal evaluation.
`main_functions.ipynb`	Provides shared computational primitives and trade maintenance routines.
`trade_conditions.ipynb`	Evaluates trade entry conditions and enforces signal idempotency.
`execute_mttf.ipynb`	Orchestrates scheduled execution and module coordination.

Table 2: Core system components and their primary responsibilities.

Table 2 provides a static, component-level overview of the core files that comprise the system, summarising their respective responsibilities. Figure X complements this by illustrating the dynamic execution flow, showing how these components are orchestrated at runtime through a scheduled, state-aware pipeline (Figure 9).

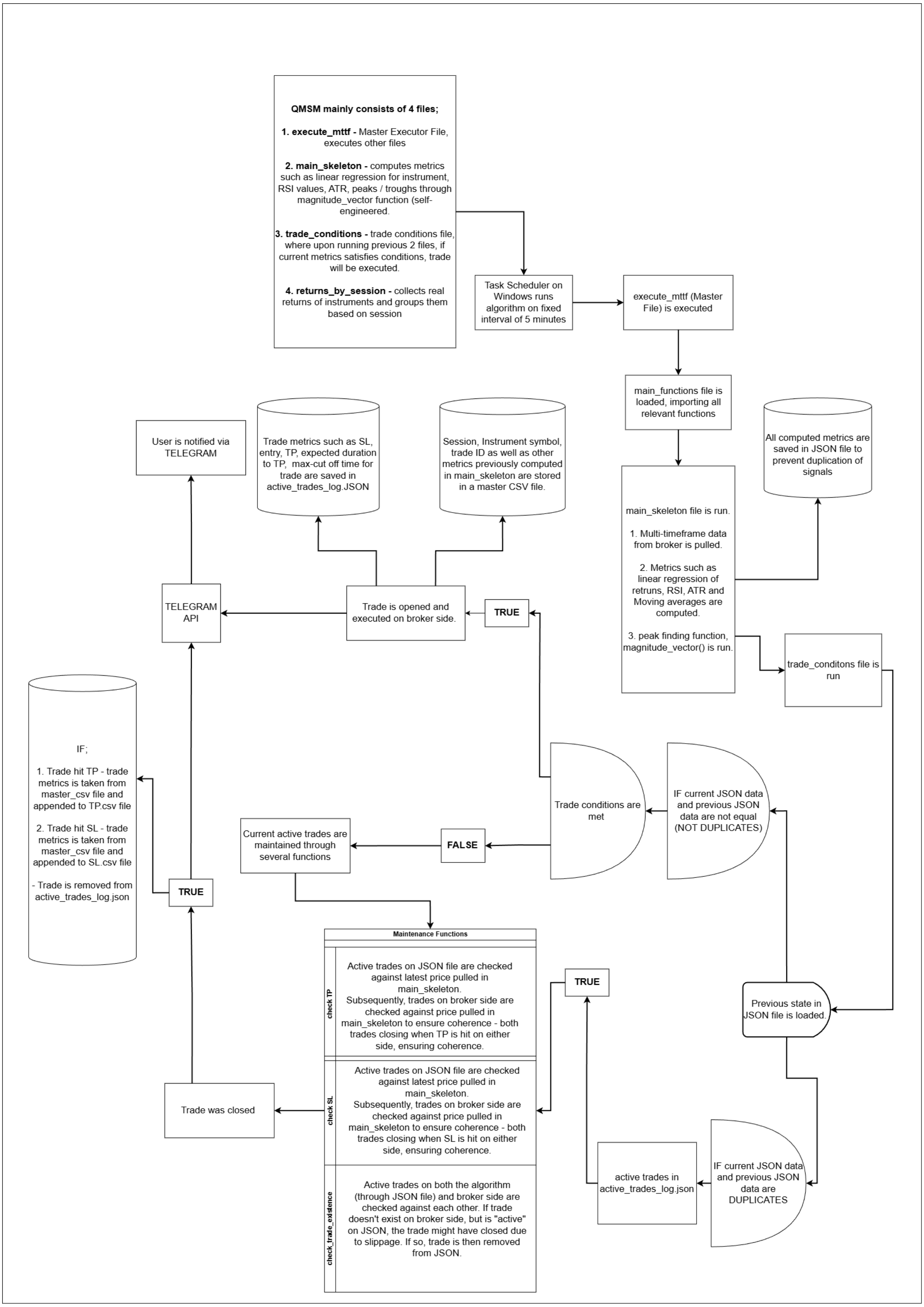

Figure 9: Algorithm process flow and pipeline.

Live Deployment

The system has been deployed live on demo accounts, operating under conditions that closely mirror real execution environments. Trade lifecycle management is handled through an independent JSON-based state-tracking mechanism that is explicitly decoupled from broker-side state. To ensure consistency, guard routines continuously reconcile trades recorded within the algorithm against those active on the broker, preventing execution mismatches or duplicated positions.

All order-related operations are wrapped in exception-safe logic to account for partial fills, API inconsistencies, and potential state corruption. In addition, a dedicated monitoring and tooling layer is integrated via the Telegram API, providing real-time notifications for trade entries and exits, signal generation, and detailed diagnostics for execution failures or state anomalies (e.g., JSON corruption or broker–algorithm desynchronisation)

An example of a notification sent through telegram can be seen in Figure 10.

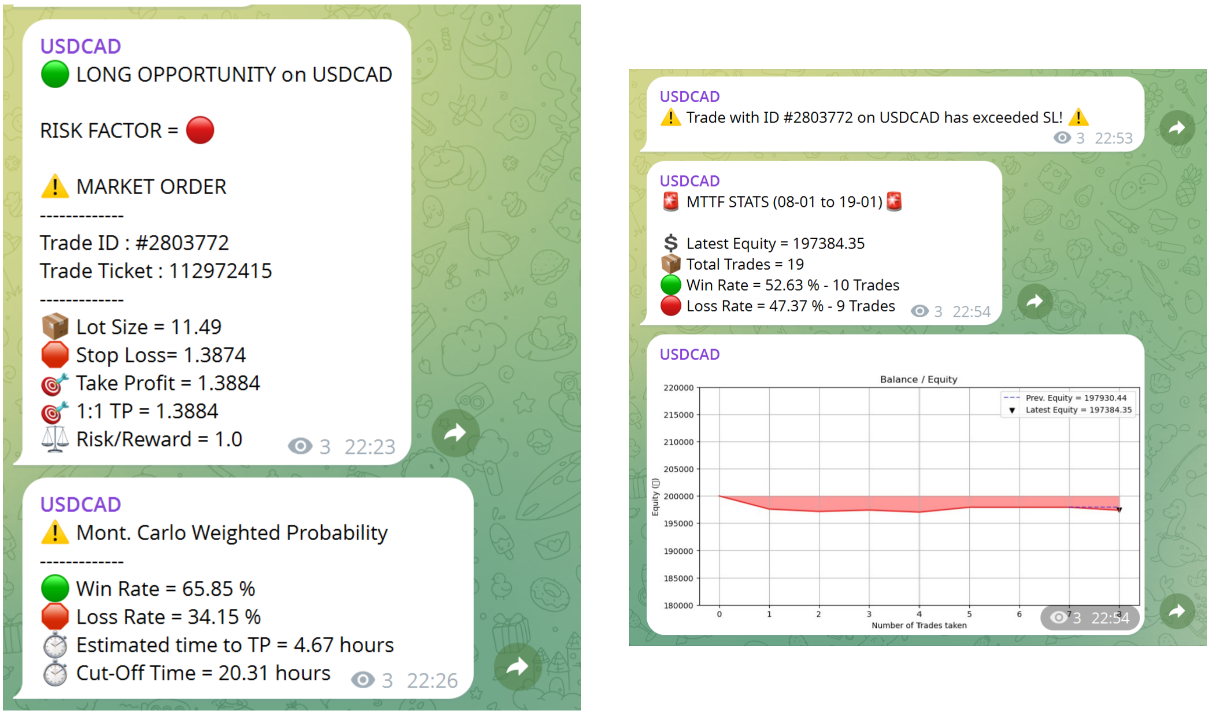

Figure 10: Examples of notifications being sent on Telegram.

Known Limitations & Risk Factors

While the algorithm has been designed to adapt to prevailing market conditions as robustly as possible, certain failure modes are unavoidable under live trading conditions. These limitations arise both from strategic assumptions inherent to the model and from practical constraints imposed by real-time execution, data availability, and system-level engineering considerations.

- **Regime Mismatch**: prolonged compression in volatility reduces signal frequency and quality.
- **Data Feed Integrity & Temporal Consistency**: stalled data on a specific timeframe, but continuous update on other timeframes. Thus, resulting in stale state variables, delayed signal generation, or misaligned execution logic if not explicitly detected.
- **Feature Non-Stationarity**: volatility-normalised features may drift under structural market changes.
- **Loss - Clustering**: clustered signals can increase portfolio-level drawdown risk.
- **Slippage:** The risk–reward (RR) estimated at signal generation may not reflect realised execution conditions. Entry prices are computed using the most recently completed bar (i.e., `r["close"].iloc[-1]`), which updates at fixed intervals rather than on a tick-by-tick basis. As a result, trades may be opened at prices that differ from the estimated entry level, leading to deviations between expected and realised RR.

Current Status & Forward Testing

The algorithm has been deployed live since 08-01-2026. Over this period, performance has been broadly breakeven, with certain weeks generating modest profits that were subsequently offset in following weeks. This behaviour remains consistent with expectations derived from prior portfolio simulations using USDCAD, GBPUSD, and the S&P 500, where extended periods of stagnation were observed before cumulative or excess R turned positive—often. For example, the first month of the portfolio only turning positive after approximately 25 trades in the first two months of 2018.

During the first week of live deployment, a flaw in the trade condition logic resulted in the algorithm opening seven identical trades on GBPUSD within a short time window. These trades were not intended to be simultaneously active under the designed strategy logic. The resulting cluster of unintended positions led to an abnormal drawdown, with cumulative R declining to approximately -7R. The issue was promptly identified, diagnosed, and resolved, and has not reoccurred as of the time of writing.

Excluding these seven anomalous trades, a total of 19 trades were executed under correct operating conditions. Within this subset, the win–loss distribution was approximately balanced at 50% each, resulting in near breakeven performance. Despite this, the account remains at an overall loss of approximately -3R, largely attributable to losses incurred during trades entered at the lower bound of the allowable risk–reward threshold (minimum entry of 0.8R).

A summary of closed trades during the live period is presented in Figure 11.

Trades	Trade ID	Trade Ticket	Datetime	Session	Instrument	Type of Trade	RSI at peak/trough	Peak/Trough Z-Score	m15_slope	h1 log returns	m15 log returns	m5 log returns	m1 log returns	Trade Size	close std	atr_std	est. duration to tp/hrs	est. cut-off duration to tp	lot_size	S/L	Entry	T/P	win rr	loss rr	trade duration /hrs	Outcome
1	#1787563	110314790	2026-01-12 19:04:38	EU	US500.cash	Long	30.61	0.16	0.060262	4.510637	1.75292	1.152409	0.155912	0.004289	0.004377	0.00024	18.08	34.96	23.59	6904.37	6919.67	6934.05	0.94	1.06	3.45	1
2	#8755301	110843944	2026-01-13 21:20:50	US	USDCAD	Long	41.42	0.15	4.91E-06	-1.16803	0.713126	1.227424	-0.06543	0.002161	0.003842	7.56E-05	8.17	28.64	2.38	1.3863	1.38795	1.3893	0.82	1.18	0.2	0
3	#9809421	111010827	2026-01-13 23:55:51	US	USDCAD	Long	50.15	2.28	5.08E-06	-1.17685	0.73829	1.194195	-0.00412	0.002594	0.003769	7.71E-05	2.08	25.96	2.2	1.386	1.3878	1.3896	1	1	1.87	1
4	#9027837	111223876	2026-01-14 12:56:24	ASIAN	US500.cash	Long	29.46	1.17	0.073787	4.415489	2.143467	1.175981	-0.2852	0.007359	0.004336	0.000207	7.5	29.41	13.48	6925.73	6952.43	6976.89	0.92	1.08	9.61	0
5	#5119332	111393564	2026-01-14 21:10:57	US	USDCAD	Long	30.33	0.03	6.57E-06	-1.27635	0.954091	0.966633	0.10579	0.003603	0.003246	8.04E-05	21.75	48.74	1.83	1.385	1.3876	1.39	0.92	1.08	23.87	1
6	#1648867	111641729	2026-01-15 03:35:53	US	USDCAD	Long	45.43	0.44	6.95E-06	-1.30445	1.008771	0.869785	-0.03094	0.002379	0.003036	7.66E-05	12.17	36.21	2.86	1.3856	1.38725	1.3889	1	1	17.45	1
7	#8027370	111635135	2026-01-15 03:10:50	US	USDCAD	Long	45.43	0.44	6.92E-06	-1.30435	1.004828	0.8781	-0.02097	0.00245	0.003054	7.66E-05	21.92	46.11	2.59	1.3859	1.38772	1.3893	0.87	1.13	17.87	1
8	#2803772	112972415	2026-01-19 22:26:10	US	USDCAD	Long	41.99	0.25	1.09E-05	-1.54821	1.581695	0.18962	-0.05894	0.000721	0.000977	7.38E-05	4.67	20.31	11.49	1.3874	1.3879	1.3884	1	1	0.46	0
9	#5479259	113484187	2026-01-20 23:35:50	US	GBPUSD	Short	57.72	2.83	-2.4E-06	0.627252	-0.35998	-0.28365	0.531586	-0.00431	0.002267	0.000108	7.95	43.46	1	1.3496	1.34644	1.3438	0.84	1.16	3.53	1
10	#5199256	114135447	2026-01-22 03:37:28	US	US500.cash	Short	73.22	3.78	0.021024	3.973499	0.609027	-2.35421	-0.17498	-0.00777	0.008269	0.000297	9.93	45.24	14.09	6901.65	6874.37	6848.21	0.96	1.04	0	1
11	#7908437	114187746	2026-01-22 07:11:37	ASIAN	US500.cash	Short	59.51	2.03	0.019087	3.96536	0.552849	-2.3762	0.193414	-0.00547	0.008255	0.000314	4.61	41.45	19.72	6913.81	6894.33	6876.11	0.94	1.06	9.52	0
12	#4120797	114287055	2026-01-22 15:52:18	EU	US500.cash	Short	58.76	-0.27	0.01193	3.94835	0.345444	-2.26873	1.648275	-0.00556	0.008134	0.000316	6.08	42.11	19.46	6913.71	6893.97	6875.35	0.94	1.06	0.84	0
13	#6348744	114512973	2026-01-22 23:41:31	US	US500.cash	Short	51.25	1.98	0.006963	3.938504	0.201572	-1.97174	1.960624	-0.00637	0.007856	0.000312	7.01	41.47	16.58	6933.49	6911.03	6889.47	0.96	1.04	2.19	0
14	#3439023	114669840	2026-01-23 08:46:51	ASIAN	US500.cash	Short	43.83	-0.28	0.003796	3.928593	0.109855	-1.64276	1.435917	-0.0063	0.007586	0.000307	12.37	50.47	15.97	6939	6915.73	6895.46	0.87	1.13	9.02	1

Figure 11: List of closed trades excluding the duplicated GBPUSD trades.

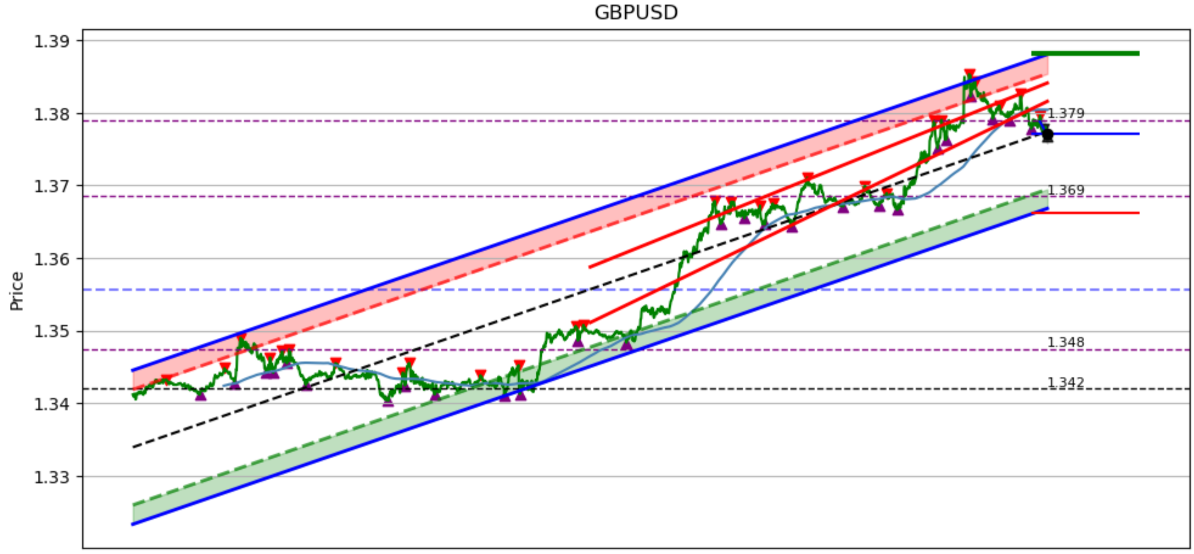

Figure 12: A snapshot of the algorithm.