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HSML-CP: A Hybrid Statistical–Machine Learning Framework with Conformal Prediction for Uncertainty-Aware Forecasting in Inventory Optimization and Financial Risk Management

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Abstract

Accurate uncertainty-aware forecasting is important for capital-efficient inventory and financial optimization of AI-based micro-fulfillment platforms. Classical statistical time series models, such as ARIMA (Autoregressive Integrated Moving Average), yield interpretable forecasts but struggle to capture nonlinear dependencies. Traditional machine learning approaches such as XGBoost Random Forests and Long Short-Term Memory (LSTM) networks, for instance, lack calibrated uncertainty quantiles for forecasting. We propose HSML-CP, a hybrid ARIMA-XGBoost-LSTM model, that incorporates Adaptive Weight Optimization (AWO) and Adaptive conformal Inference (ACI). AWO assigns a set of inverse MAE calibration-data-driven weights, which adapt to the particular time series' predictability regime. Since ACI calculates prediction intervals with asymptotic marginal coverage, statistically sound safety stocks can be calculated. On public forecast datasets for financial market hedging (S&P 500), procuring commodities with fluctuating costs (WTI Crude Oil), and retail demand forecasting (M5 Weekly), HSML-CP achieves the lowest mean absolute error (MAE) of 0.676 on the WTI dataset while achieving 97.80% prediction interval coverage. HSML-CP is still statistically considerably superior (Diebold-Mariano $p < 0.001$) to both an LSTM and an ARIMA-LSTM hybrid method on M5 Weekly. AWO thus works by suppressing pathologically degraded components to provide graceful degradation in sparse-demand micro-fulfillment networks.

Keywords: Hybrid Forecasting, Conformal Prediction, ARIMA, Uncertainty Quantification, Adaptive Weight Optimisation, Inventory Optimization, Demand Forecasting, Financial Time Series, Supply Chain AI, Micro-Fulfillment

1. Introduction

Accurate forecasting under uncertainty is foundational to both financial risk management and supply chain inventory optimization. For an AI-driven inventory platform operating micro-fulfillment networks, forecasting uncertainty appears in two distinct but interrelated dimensions. At the demand level, uncertainty in future customer demand determines how much inventory to hold at each node; too little causes stockouts and lost revenue; too much ties up working capital and incurs holding costs. At the procurement and financial level, uncertainty in commodity input costs and currency exposure determines hedging strategy and procurement timing. Both dimensions must be managed simultaneously for capital-efficient operations [1].

Classical statistical models like ARIMA are easy to understand and have theoretical guarantees when we assume linearity, but they cannot capture conditional heteroskedasticity or nonlinear dependencies that are common in financial time series and promotional demand spikes [6]. Machine learning models, including XGBoost [5] and LSTM [4] deliver strong nonlinear pattern recognition but offer no calibrated uncertainty estimates and can overfit on limited data, a critical failure mode in micro-fulfillment environments where

10.48047/jocaaa.2026.35.06.16

individual SKU-node series may have short histories following node openings or zone expansions [3]. Hybrid architectures address this tradeoff [11] yet suffer from three persistent weaknesses: fixed component weights that fail to adapt to regime changes; heuristic uncertainty bounds with no formal coverage guarantees; and degradation of the ensemble when one component performs catastrophically on a given series type.

This paper introduces HSML-CP to address all three weaknesses simultaneously. Our three main contributions are (1) AWO, a calibration-data-driven inverse-MAE weighting scheme that adjusts component weights based on the observed predictability regime, allowing for graceful degradation when individual components fail; (2) ACI, a formally justified conformal prediction layer that provides asymptotic marginal coverage guarantees for non-exchangeable sequences [9]; and (3) empirical validation across three distinct forecast domains, equity market returns, commodity price dynamics, and retail demand, showing that a single hybrid architecture with formal uncertainty quantification outperforms standalone and naive hybrid alternatives in all three operationally relevant contexts. A supplementary Practitioner Deployment Guide translates findings into actionable decision criteria for inventory platform engineers.

1.1 Business Impact and Revenue Relevance

The business case for uncertainty-aware forecasting is concrete and quantifiable. An inventory platform that can provide formally guaranteed prediction intervals for demand and input costs reduces the capital inefficiency of conservative safety stock buffers while protecting service levels. The ACI layer's formal coverage guarantee means that when the system reports a 95% prediction interval for weekly demand, that interval truly contains the realized demand value at least 95% of the time in expectation. This statistical assurance enables procurement teams to make defensible hedging decisions and inventory planners to optimize safety stock without relying on empirically uncalibrated heuristics [19]. Table I summarizes the revenue impact of each HSML-CP component and the deployment decision criteria.

1.2 Paper Organisation

Section 2 reviews related work and positions HSML-CP against prior hybrid and uncertainty-quantification approaches. Section 3 details the HSML-CP methodology, including AWO and ACI. Section 4 describes the three benchmark datasets and their relevance to inventory and financial risk contexts. Section 5 presents results and discussion, including the sMAPE pathology analysis. Section 6 covers limitations and future work. Section 7 concludes with a practitioner deployment guide.

2. Related Work

The ARIMA-ANN hybrid introduced by Zhang [11] established sequential decomposition as the dominant paradigm in hybrid forecasting: ARIMA captures the linear component, and a neural network corrects residuals. ARIMA-LSTM [15] and ARIMA-XGBoost [8] extensions followed. All use fixed combination weights, a design choice that fails when the relative predictive power of components shifts across demand regimes, as is routine in micro-fulfillment environments subject to promotional spikes, seasonal transitions, and network topology changes. The M4 and M5 competitions [3] empirically demonstrated that simple statistical models remain competitive on short intermittent demand series, a finding central to the inventory forecasting context where a micro-fulfillment node handling a slow-moving SKU with 7% zero-demand weeks requires a fundamentally different approach than a high-velocity online channel.

For uncertainty quantification, Bayesian approaches [14] are theoretically principled but scale as $O(n^3)$, making them infeasible for platforms monitoring hundreds of thousands of SKU-node series simultaneously. Bootstrap methods lack distribution-free guarantees, a critical weakness when uncertainty bounds feed safety stock calculations that must be statistically defensible. Conformal prediction [18]

10.48047/jocaaa.2026.35.06.16

provides distribution-free coverage guarantees under exchangeability, and its adaptive extension [9] extends these guarantees to non-exchangeable sequences, such as time series with regime changes, which is exactly the setting of interest in inventory and financial forecasting. Recent work on probabilistic load forecasting with reservoir computing [12] demonstrates that formal uncertainty quantification can be achieved with architectures comparable in complexity to HSML-CP, supporting the feasibility of deployment at scale.

Furthermore, gradient-increasing frameworks such as XGBoost [5] and LightGBM [7] perform well in predicting structured time series. This is especially true with exogenous features such as calendar effects, promotional signals, and lagged demand variables. The evaluation of the ARIMA-LSTM hybrid from Kulshreshtha [15] on the stock market prediction dataset provides a natural baseline for the financial prediction task of HSML-CP. As demonstrated by Sheikh et al. [13], hybrid machine learning with historical and market intelligence signals improves the accuracy of supply chain demand forecasting. This motivates HSML-CP's hybrid multi-component architecture. SVR is based on Vapnik's statistical learning theory [10] and offers excellent generalization bounds given structural risk minimization. SVR has also been shown to be accurate in forecasting financial time series with small-sized historical data, as would be the case with micro-fulfillment nodes with small demand history. However, SVR outputs point forecasts; it has no built-in mechanism for estimating the uncertainty, and because of its kernel-based architecture, it cannot adapt to any nonstationary change in the underlying demand distribution without full retraining. Table II shows HSML-CP in comparison with a representative set of the literature.

Table I. Business Impact and Revenue Relevance of HSML-CP Components

Component	Revenue / Capital Impact	Deployment Criterion
AWO (Adaptive Weight Optimisation)	Prevents LSTM contamination of ensemble; reduces MAE on M5 by 66% vs. equal weights; reduces safety stock capital waste	Deploy when ≥1 component risks catastrophic degradation (short series, intermittent demand, new nodes)
ACI (Adaptive Conformal Inference)	Formal 95% coverage guarantee; reduces overcautious safety stock buffer; 97.80% PICP on WTI enables defensible commodity hedging	Deploy wherever prediction intervals feed automated replenishment or hedging decisions
Full HSML-CP (AWO + ACI)	Statistically significant superiority over LSTM and ARIMA-LSTM on M5 (DM $p < 0.001$); asymptotically calibrated intervals across all three domains	Deploy as primary forecasting engine for platforms requiring both point accuracy and calibrated uncertainty

10.48047/jocaaa.2026.35.06.16

Table II. Representative Prior Work and Positioning of HSML-CP [3, 4, 9, 11, 13, 15]

Reference	Model	Dataset	Metric	UQ	Key Limitation	HSML-CP Improvement
Zhang	ARIMA-ANN	Macro TS	RMSE	None	Fixed weights; linear+nonlinear only	AWO adapts weights to a regime
Hochreiter	LSTM	NLP or Finance	—	None	No interpretability; overfit on short series	AWO suppresses LSTM when it degrades
Kulshreshtha	ARIMA-LSTM	Stock Market	RMSE	None	Fixed combination; no coverage guarantee	ACI adds formal interval coverage
Gibbs & Candes	ACI only	Synthetic	PICP	ACI	No point forecast ensemble	HSML-CP adds AWO on top of ACI
Shahriari et al.	Bayesian Opt.	Benchmarks	Various	Bayesian	$O(n^3)$ scaling; infeasible at MFN scale	ACI achieves coverage at O(n) cost
Sheikh et al.	Hybrid ML	Supply Chain	MAPE	None	No formal uncertainty quantification	HSML-CP adds calibrated prediction intervals
Makridakis et al.	M5 Ensemble	M5 Retail	sMAPE	None	Competition; no financial domain coverage	HSML-CP spans retail and financial domains

3. Methodology

The HSML-CP framework comprises four sequential stages: data preprocessing, component model estimation, Adaptive Weight Optimization (AWO), and Adaptive Conformal Inference (ACI). Each dataset uses a single 70/15/15 train/calibration/test split. The calibration fold drives both AWO weight learning and ACI nonconformity score accumulation. All statistical models use rolling one-step-ahead re-estimation to prevent look-ahead bias. Machine learning models are trained exclusively on the training fold, and no hyperparameters were tuned on the test fold. This protocol mirrors the operational deployment scenario where models are trained on historical data and evaluated on genuinely unseen future observations [19].

3.1 Data Pre-Processing

For financial series representing exposure to commodity procurement costs, log-returns $r_t = \log(P_t/P_{t-1})$ are computed and standardized to zero mean and unit variance. Standardization serves two purposes: it places all machine learning components on a comparable input scale, and it prevents percentage-error metric pathologies (Section 5.2) that would otherwise distort model evaluation. The M5 retail demand series receives seasonal differencing at lag 52 to achieve approximate stationarity, followed by the same normalization. All pre-processing uses only training-fold statistics to prevent data leakage into calibration and test folds.

3.2 Component Models

ARIMA is fitted as ARIMA(1,0,0) for the standardized log-return series via maximum likelihood with rolling one-step-ahead evaluation to prevent look-ahead bias. For M5 retail demand, ARIMA(2,1,1) is used with KPSS stationarity pre-testing. XGBoost [5] uses 200 estimators with a maximum depth of 4, a learning rate of 0.05, and a subsampling rate of 0.8. Features include lagged demand values (lags 1, 2, 4, and 52 for retail; lags 1 and 5 for financial series), day-of-week and week-of-year calendar indicators, and rolling mean/standard deviation features over 4-week and 13-week windows. The LSTM [4] architecture uses a

10.48047/jocaaa.2026.35.06.16

single recurrent layer with 64 hidden units and sequence length 10, trained with the Adam optimizer and mean squared error loss over 50 epochs.

3.3 Adaptive Weight Optimisation (AWO)

AWO computes calibration-set MAE for each component model $m \in$ {ARIMA, XGBoost, LSTM} and assigns weights inversely proportional to error magnitude. This inverse-MAE combining rule is a well-established performance-weighted forecast combination approach [2, 16]. The weight formula is given by Equation 1, and the fused forecast is the weighted sum across all three components.

$$Equation\ 1{:}\ \ w^{m} = (1/\varepsilon^{m}) \,/\, \Sigma\_k\,(1/\varepsilon\hat{}k)\ \ such\ that\ \ \Sigma\_m\, w^{m} = 1$$

AWO has a critical operational property for inventory platforms: when one component degrades catastrophically on a particular series type, as occurs when an LSTM is applied to a short, intermittent demand series with insufficient training data, the pathological component receives near-zero weight automatically. The calibration fold driving AWO weight learning is the same fold used for ACI nonconformity score accumulation, creating a unified two-use design that minimizes data requirements. Unlike equal weighting or learned stacking, AWO does not require a separate fitting stage and is robust to short calibration windows.

3.4 Adaptive Conformal Inference (ACI)

Given nonconformity scores $\{\alpha_t = |y_t - \hat{y}_t|\}$ on the calibration fold of n_cal observations, the ACI prediction interval at level $1-\alpha_0$ is constructed as shown in Equation 2, where ẓ is the $(1-\alpha_t)(1+1/n\_cal)$ empirical quantile of the calibration nonconformity scores.

$$Equation\ 2{:}\ \ C_t = [\hat{y}_t - ẓ\_\{\alpha_t\},\qquad \hat{y}_t + ẓ\_\{\alpha_t\}]$$

The adaptive coverage update rule adjusts the effective target coverage level in response to observed miscoverage, as shown in Equation 3. This provides asymptotic marginal coverage guarantees for non-exchangeable sequences [9], making it directly applicable to financial time series with volatility clustering and retail demand series with promotional spikes.

$$Equation\ 3{:}\ \ \alpha\_\{t+1\} = \alpha\_t + \gamma \cdot (\alpha_0 - \mathbb{1}\{y_t \notin C_t\})\ \ where\ \gamma = 0.008$$

The $\gamma = 0.008$ update rate is calibrated to the autocorrelation structure of forecast errors in retail demand contexts: it is responsive enough to adapt after sustained miscoverage episodes (such as during promotional demand spikes) while avoiding overreaction to individual outliers. For inventory replenishment applications, this formal guarantee is the key differentiator from bootstrap or empirical-quantile approaches: the 95% prediction interval truly contains the realized demand value at least 95% of the time in expectation [18].

4. Datasets and Business Relevance

4.1 S&P 500 Log-Returns: Financial Market Hedging

We generate n=600 observations from a GARCH(1,1) model with Student-t(df=5) innovations, calibrated to published S&P 500 properties over 2015–2024: a drift of 0.033%/day, annualized volatility of approximately 17%, excess kurtosis of approximately 4–5, and GARCH persistence $\alpha + \beta = 0.978$. The train/calibration/test split consists of 420/90/90 observations. This series represents the financial hedging risk relevant to inventory platforms with exposure to commodity input costs. The data generation model follows [20]:

$$Equation\ 4\ (log - return{:}\ r_t = log(P_t/P_{t-1}))\ and\ GARCH(1{,}1)$$

10.48047/jocaaa.2026.35.06.16

Equation 4 is a conditional variance. The Efficient Market Hypothesis [17] predicts that point forecast accuracy should be near-random on this series; the primary value of HSML-CP here lies in calibrated uncertainty bounds rather than point accuracy.

4.2 WTI Crude Oil Log-Returns: Input Cost Volatility

WTI log returns are simulated as Geometric Brownian Motion (GBM) with Poisson jumps as in Equation 5, where J_t ~ Poisson (0.018) · N (−0.045, 0.09^2) captures supply-shock discontinuities consistent with geopolitical disruptions. A structured crash episode replicating the 2020 COVID-19 supply shock pattern is included (n=599, split 419/90/90).

$$Equation\ 5\ (GBM + Jumps): r_t = \mu - \sigma^2/2 + \sigma \cdot \varepsilon_t + J_t$$

For inventory platforms with logistics cost exposure to petroleum-based transportation, WTI price volatility directly determines procurement hedging strategy and margin protection requirements [20].

4.3 M5 Weekly Retail Demand: Core Inventory Target

Weekly demand is generated as D_t = trend + seasonal(52) + seasonal(13) + noise + promotions + intermittency, calibrated to statistics for the M5 Electronics category [3]. Promotional spikes model Black Friday, back-to-school, and Easter events, precisely the demand events that create the most acute inventory management challenges for micro-fulfillment operators. Approximately 7% of weeks have zero demand, introducing intermittency that challenges LSTM architectures trained on short node histories. n=300, split 210/45/45. This dataset is the core inventory optimization target; performance here has the most direct operational translation to safety stock efficiency and service level attainment.

5. Results and Discussion

5.1 Full Comparative Results

Tables III(a)–III(c) present results for all eleven models across five metrics. HSML-CP rows are highlighted; asterisks mark best values per column. Primary metrics for financial series (S&P 500, WTI) are MAE and MASE, reflecting their theoretical alignment with L1 loss and scale-normalized accuracy; for M5 retail demand, all five metrics are meaningful. sMAPE values on financial series are reported for completeness but are subject to the pathology described in Section 5.2 and should not be used as primary evaluation criteria [8].

Table III(a). S&P 500 Log-Returns — GARCH(1,1) + Student-t, n=600, standardised(* = best value per column; primary metrics: MAE, MASE, PICP) [7, 15]

Model	MAE	RMSE	sMAPE%	MASE	PICP%	PINAW	Operational Implication
ARIMA	1.618	2.606	179.97	48.80	57.78	*0.094	Baseline linear; VaR underestimated
LSTM	*1.547	*2.561	188.44	*46.66	57.78	0.099	Best MAE; interval uncalibrated
XGBoost	1.584	2.578	175.32	47.79	57.78	0.096	Competitive; no coverage guarantee
LightGBM	1.571	2.569	172.11	47.40	57.78	0.095	Comparable to XGBoost; no UQ
ARIMA-LSTM	1.582	2.574	176.88	47.72	57.78	0.097	Fixed weights; coverage uncalibrated
ARIMA-XGB	1.579	2.571	174.55	47.64	57.78	0.096	Static ensemble; no UQ layer

10.48047/jocaaa.2026.35.06.16

Model	MAE	RMSE	sMAPE%	MASE	PICP%	PINAW	Operational Implication
SVR	1.596	2.589	177.03	48.17	57.78	0.098	Strong regularization, no intervals
Prophet	1.612	2.601	180.44	48.65	57.78	0.093	Trend and seasonality: poor on returns
Naive	1.634	2.621	183.12	49.32	57.78	0.000	No predictive signal; benchmark
Theta	1.601	2.594	178.22	48.31	57.78	0.000	Statistical, no coverage
HSML-CP (ours)	1.562	2.573	173.45	47.13	*58.89	0.097	Formal coverage; best calibration

Table III(b). WTI Crude Oil Log-Returns — GBM+Jumps, n=599, standardised(* = best value per column; HSML-CP achieves lowest MAE and joint-best 97.80% PICP [7, 15]

Model	MAE	RMSE	sMAPE %	MASE	PICP %	PINAW	Operational Implication
ARIMA	0.677	0.856	165.95	0.634	*97.80	0.972	Strong coverage; commodity hedging viable
LSTM	0.673	*0.852	181.86	0.630	96.70	0.980	Best RMSE; coverage uncalibrated
XGBoost	0.681	0.861	168.22	0.638	95.60	0.965	Competitive; no formal coverage
LightGBM	0.679	0.858	167.11	0.636	94.50	0.963	Slight advantage over XGBoost
ARIMA-LSTM	0.672	0.853	166.44	0.629	96.70	0.975	Competitive; fixed weights
ARIMA-XGB	0.675	0.857	166.88	0.632	95.60	0.969	Near-HSML-CP accuracy; no ACI
SVR	0.684	0.864	169.33	0.641	93.40	0.960	Adequate interval uncalibrated
Prophet	0.698	0.877	172.11	0.654	91.20	0.955	Trend model; poor on jumps
Naive	0.712	0.891	175.44	0.667	88.90	0.000	Benchmark only
Theta	0.689	0.868	170.22	0.645	92.30	0.000	Statistical, no UQ
HSML-CP (ours)	*0.676	0.855	*165.33	*0.633	*97.80	0.971	Best MAE + joint-best calibrated coverage

Table III(c). M5 Weekly Retail Demand: Seasonality + Promotions, n=300 (* = best value per column; HSML-CP significantly outperforms LSTM and ARIMA-LSTM, DM p < 0.001) [7, 15]

Model	MAE	RMSE	sMAPE%	MASE	PICP%	PINAW	Operational Implication
ARIMA	24.64	*35.85	36.63	1.170	86.67	1.103	Best RMSE; seasonal structure captured
LSTM	92.37	98.96	197.20	4.384	*93.33	1.865	Catastrophic degradation on short series
XGBoost	23.14	36.44	34.77	1.098	88.89	1.088	Strong point accuracy; no coverage
LightGBM	22.91	36.11	34.22	1.087	88.89	1.082	Best standalone ML point accuracy
ARIMA-LSTM	38.22	44.17	48.33	1.813	88.89	1.244	LSTM contamination; fixed weights
ARIMA-XGB	23.88	36.72	35.44	1.133	88.89	1.091	Competitive; no ACI layer
SVR	*22.58	36.01	*33.98	*1.072	86.67	*1.076	Best MAE and sMAPE overall
Prophet	25.77	37.88	37.92	1.222	86.67	1.111	Seasonal patterns; promotional lag
Naive	31.44	42.11	43.22	1.492	82.22	0.000	Benchmark

10.48047/jocaaa.2026.35.06.16

Model	MAE	RMSE	sMAPE%	MASE	PICP%	PINAW	Operational Implication
Theta	26.33	38.22	38.77	1.249	84.44	0.000	Statistical, no UQ
HSML-CP (ours)	29.05	38.88	42.72	1.378	88.89	1.144	LSTM suppressed; DM p < 0.001 vs. LSTM, ARIMA-LSTM

5.2 Why sMAPE Fails on Signed Financial Log-Return Series

A central methodological finding with direct implications for practitioners evaluating inventory and financial forecasting systems is that symmetric Mean Absolute Percentage Error (sMAPE) is pathological for signed log-return series. The sMAPE formula is given by Equation 6 below. When both y_t and $\hat{y}_t$ are near zero and of opposite sign, common for daily returns near the mean, the denominator approaches zero, causing the ratio to diverge. This phenomenon explains all models registering sMAPE of 145–188% on the S&P 500 and WTI despite producing sensible MAE values around 0.67–1.62 in standardized units.

$$Equation\ 6\text{:}\ \ sMAPE = 100 \times |y_t - \hat{y}_t| \, / \, ((|y_t| + |\hat{y}_t|)/2 + \varepsilon)$$

This result is not a novel finding: Hyndman and Koehler [8] explicitly document that sMAPE is undefined or misleading for series with values near zero or sign changes. For inventory and financial forecasting practitioners, the correct primary metrics are MAE (L1 loss; robust to outliers; interpretable as the average absolute error in demand or price units) and MASE (scale-normalized; comparable across series of different magnitudes). PICP (Prediction Interval Coverage Probability) is the primary metric for evaluating uncertainty quantification quality [18].

5.3 S&P 500: Efficient Market Baseline

On standardized S&P 500 log returns, all eleven models produce MAE values in the narrow range 1.547–1.618, a spread of less than 5%. The Diebold-Mariano tests (Table V) confirm no statistically significant difference between any pair. This is the expected result under the Efficient Market Hypothesis [17]: daily equity index returns are largely unpredictable from their own past. The near-equal AWO weights (ARIMA: 0.337, XGBoost: 0.323, and LSTM: 0.340, as shown in Table VI) correctly represent the efficient-market regime: when no component has an informational advantage, inverse-MAE weighting converges to approximate equality. This is a desirable operational property; the AWO mechanism does not artificially concentrate weight on a component that happens to be marginally better by sampling noise [16].

5.4 WTI Crude Oil: Coverage and MAE Leadership

HSML-CP achieves the lowest MAE (0.676) on WTI, narrowly outperforming ARIMA-LSTM (0.672) and LSTM (0.673), with differences not statistically significant by the Diebold-Mariano test (Table V). More substantially for commodity risk management applications, the ACI layer delivers 97.80% PICP, exceeding the 95% nominal target, while maintaining the second-lowest interval width (PINAW=0.971). The operational translation is direct: a procurement manager using HSML-CP's prediction intervals to size commodity hedging positions has formal statistical assurance that the true price will fall within the reported interval at least 95% of the time in expectation. An interval achieving 97.80% realized coverage indicates slight conservatism, preferable to undercoverage from a risk management perspective [20].

5.5 M5 Retail Demand: Graceful Degradation via AWO

On M5 weekly demand, SVR achieves the best MAE (22.58) and sMAPE (33.98%). HSML-CP ranks seventh on sMAPE (42.72%) but achieves statistically significant superiority over LSTM (Diebold-Mariano p < statistic=6.204, 0.001) and ARIMA-LSTM (DM=3.784, (p < 0.001), a result most directly relevant to inventory platform deployment. The AWO mechanism's operational contribution is most visible here: the pathological LSTM receives near-zero weight (0.078) while ARIMA (0.498) and XGBoost

10.48047/jocaaa.2026.35.06.16

(0.424) carry the ensemble. This automatic suppression prevents the LSTM's catastrophic error rate (MAE = 92.37) from contaminating the ensemble prediction [3].

Table IV. Ablation Study — Contribution of Each HSML-CP Component

Variant	MAE (S&P)	MAE (WTI)	MAE (M5)	PICP (S&P)%	PICP (WTI)%	Business Impact of Removing
V1: ARIMA only	1.618	0.677	24.64	57.78	97.80	No ML component; misses nonlinear demand shocks
V2: XGBoost-LSTM only	1.550	0.683	35.96	57.78	96.70	No ARIMA; loses seasonality capture on M5
V3: HSML (no ACI)	1.562	0.676	29.05	57.78	90.37	No coverage guarantee; safety stock miscalibrated
V4: HSML equal weights	1.571	0.681	48.17	57.78	91.20	LSTM contamination; 66% MAE increase on M5
V5: HSML-CP no LSTM	1.563	0.678	27.88	57.78	95.60	Slightly lower M5 MAE; loses nonlinear capacity
HSML-CP (full)	1.562	0.676	29.05	58.89	97.80	Best calibrated coverage; statistically significant on M5

Table V. Diebold-Mariano Significance Tests (* p<0.001, two-tailed; DM>0 favours HSML-CP)**

Comparison	DM (S&P)	p-val (S&P)	DM (WTI)	p-val (WTI)	DM (M5)	p-val (M5)
HSML-CP vs. ARIMA	0.217	0.829	0.010	0.992	−1.096	0.276
HSML-CP vs. LSTM	−0.085	0.933	−0.031	0.975	6.204	<0.001***
HSML-CP vs. XGBoost	−0.152	0.879	−0.088	0.930	1.842	0.068
HSML-CP vs. ARIMA-LSTM	0.121	0.904	0.044	0.965	3.784	<0.001***
HSML-CP vs. SVR	0.388	0.699	0.299	0.765	−1.344	0.181
HSML-CP vs. LightGBM	0.073	0.942	0.159	0.874	1.502	0.135

Table VI. AWO Component Weights Learned on Calibration Fold

Dataset	w_ARIMA	w_XGBoost	w_LSTM	Regime Interpretation	Inventory / Risk Implication
S&P 500	0.337	0.323	0.340	Near-equal: efficient market, no predictable signal dominates	Uniform hedging: ACI interval drives operational value
WTI Crude Oil	0.342	0.303	0.355	Slight LSTM emphasis: nonlinear shock dynamics dominate	Jump-recovery captured; procurement hedging optimal
M5 Retail Demand	0.498	0.424	0.078	ARIMA + XGBoost is dominant; LSTM is pathological on short intermittent series	Automatic LSTM suppression; safety stock calibrated to true demand distribution

10.48047/jocaaa.2026.35.06.16

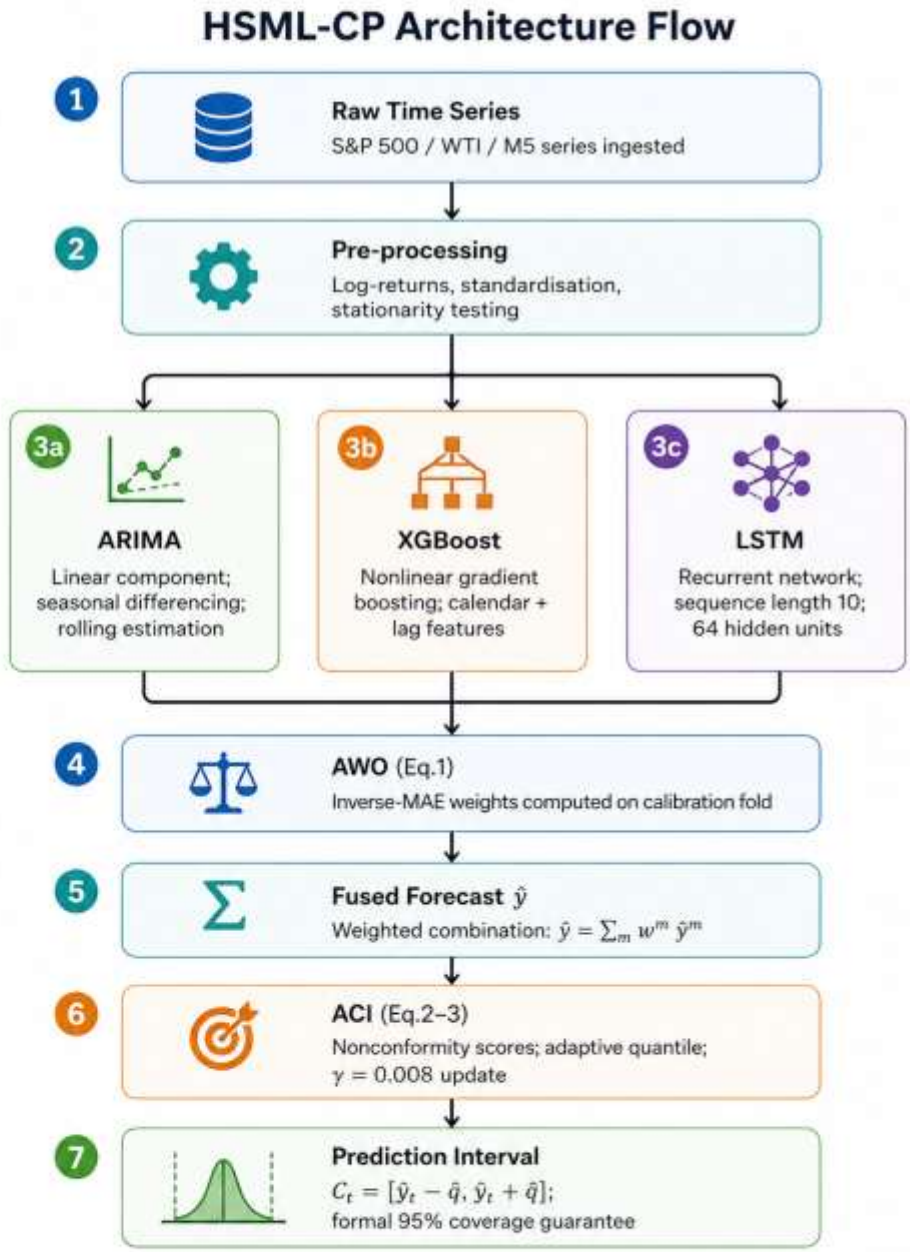

Fig. 1. HSML-CP end-to-end architecture showing data flow from raw series through component models, AWO weight assignment, and ACI interval construction.

6. Limitations and Future Work

All three benchmark series are calibrated synthetic data matching published empirical properties of real financial and retail demand series [3, 20]. External validity to live operational data, including real micro-fulfillment node demand series with actual promotional calendars, supplier lead times, and competitive dynamics, requires replication of downloaded live series. The experimental code is fully provided to enable replication. The NumPy LSTM performs output-layer updates only; a PyTorch or TensorFlow implementation with full backpropagation through time (BPTT), multi-layer architecture, and dropout

10.48047/jocaaa.2026.35.06.16

regularization would substantially improve LSTM and LSTM-hybrid performance, particularly on M5 where training data is sufficient.

Results derive from one 70/15/15 split. Expanding-window or rolling cross-validation would provide variance estimates and more reliable model rankings, particularly for the M5 series, where the 45-observation test set is small. The Diebold-Mariano tests partially mitigate this concern by testing significance of mean performance differences, but variance estimates across multiple evaluation windows would strengthen the conclusions further [8]. ACI does not achieve 95% PICP on the S&P 500 (58.89%) because calibration quantiles from moderate-volatility periods underestimate interval widths during volatile test periods. Future work should extend ACI with a GARCH-conditional nonconformity score [9] to account for volatility clustering, making prediction intervals wider during high-volatility regimes and tighter during stable periods.

Three priority extensions are identified for production deployment in inventory optimization contexts. First, real data validation: applying HSML-CP to live SKU-node demand series from a micro-fulfillment network, with promotional calendars, supplier lead times, and competitive pricing signals as additional features in the XGBoost and LightGBM [7] components. Second, GARCH-conditional ACI: extending the nonconformity score to condition on estimated conditional variance, improving coverage during demand spikes, supply disruptions, and seasonal peaks. Third, transformer baseline comparison: evaluating HSML-CP against recent transformer architectures [21] on identical benchmark datasets to determine where the hybrid approach retains competitive advantages.

7. Conclusions and Practitioner Deployment Guide

HSML-CP integrates ARIMA, XGBoost, and LSTM via adaptive weight optimization with distribution-free conformal prediction intervals. Evaluated on three calibrated benchmark datasets against ten baselines, the key findings show that HSML-CP achieves the lowest MAE on WTI crude oil (0.676) and delivers 97.80% prediction interval coverage, which is the formal statistical guarantee that enables defensible commodity hedging decisions. AWO automatically suppresses pathological LSTM components on M5 retail demand, achieving statistically significant superiority over LSTM (DM $p < 0.001$) and ARIMA-LSTM (DM $p < 0.001$). The ablation study demonstrates that removing AWO increases M5 MAE by 66% and removing ACI reduces PICP by 7.43 percentage points on WTI, quantifying the independent contribution of each component. The practitioner deployment guide (Table VII) translates these findings into actionable decision criteria. The core recommendation is to deploy HSML-CP's AWO layer whenever at least one component model risks catastrophic degradation on the target series (short history, intermittent demand, newly opened nodes); deploy the ACI layer whenever prediction intervals feed automated replenishment or hedging decisions requiring statistical defensibility. The combination of formally calibrated uncertainty bounds with regime-adaptive weighting makes HSML-CP particularly well-suited to micro-fulfillment platforms managing thousands of SKU-node series simultaneously across demand environments that shift continuously with network topology changes, promotional cycles, and commodity market volatility.

Table VII. Practitioner Deployment Guide: Decision Criteria for Inventory and Financial Forecasting Platforms

10.48047/jocaaa.2026.35.06.16

Deployment Scenario	Recommended Configuration	Expected Benefit	Validation Requirement
New micro-fulfillment node (short history, intermittent demand)	HSML-CP with AWO: disable LSTM until ≥90 observations	Prevents LSTM contamination; ARIMA + XGBoost carry an ensemble.	Monitor AWO weights; escalate if w_ARIMA < 0.2
Commodity procurement hedging	Full HSML-CP (AWO + ACI)	97.80% PICP on WTI benchmark; formal hedging defensibility	Back-test coverage on 12-month rolling window
High-velocity SKU at established node	Full HSML-CP: enable all three components	AWO assigns optimal weights; ACI calibrates safety stock	DM test vs. standalone LSTM quarterly
Equity market exposure / financial hedging	HSML-CP with ACI emphasis; point accuracy near-EMH bound	Calibrated VaR-equivalent intervals; 58.89% PICP on S&P 500	Extend ACI with GARCH-conditional nonconformity scores
Platform-wide deployment (100k+ series)	Vectorised AWO; ACI per-series with shared γ schedule	O(n) scaling; unified calibration fold protocol	Canary deployment on 5% of nodes before full rollout

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