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INELIDAMARKETSCAN
EIN WISSENSCHAFTLICHER ANSATZ FÜR ALGORITHMISCHES TRADING
Forschung und Entwicklung eines Multi-Strategie-Systems
Basiert auf ICT-Konzepten und Machine Learning

Version 1.0.1 | 2026-07-19
DVA/Reuniware Systems

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License: MIT. Schlagwörter: Algorithmisches Trading, ICT, Ichimoku, XGBoost, ML, DXY

Zusammenfassung

This document presents the research findings of the InelidaMarketScan project, an algorithmic trading system integrating ICT concepts, multi-timeframe Ichimoku analysis, and supervised ML (XGBoost). Developed in July 2026, the system comprises a 109-criteria analysis engine covering 8 timeframes, a complete ML pipeline with 111 features, a historical backtest on 3,045 trades (2025-2026), and 15 XGBoost models.

Major contributions: ICT features (FVG, OB, MSS) have zero additional predictive power compared to Ichimoku price levels (is_dxy, rr, tkx_h1 top-3 with gains 14.2, 10.0, 9.2); per-asset specialization improves OOS PF by 340% (1.173 to 4.000); FOMC Wednesdays are the 6th most important feature (gain 6.4); 50% of hours are abnormal during HIGH NEWS DAYS.

DXY native WR: 73% (233 trades). Capital simulation on 10k EUR, 1%/trade, ML% $\geq$ 50%: PF 2.27, +25,842 EUR. OOS reality: v7 PF=1.173, v13 PF=4.000 (15 trades).

1. Einleitung

1.1 Kontext und Problematik

Algorithmic trading has grown exponentially. According to the BIS (2022), automated trading accounts for over 70% of FX volumes. However, most systems rely on traditional indicators with false signal rates exceeding 70%. ICT concepts propose analyzing institutional liquidity, but their qualitative nature makes automation difficult.

1.2 Forschungsziele

1. Automate ICT + Ichimoku
2. Quantify via 109 criteria
3. Predict via XGBoost
4. Validate via OOS
5. Identify predictive factors

1.3 Dokumentenstruktur

Section 2: theory. Section 3: architecture. Section 4: Diamond Scanner. Section 5: ML pipeline. Section 6: backtest protocol. Section 7: results. Section 8: feature analysis. Section 9: anomalies. Section 10: news risk. Section 11: cross-pair. Section 12: per-asset. Section 13: trading guide. Section 14: limitations. Section 15: conclusion.

2. Theoretische Grundlagen

2.1 ICT-Konzepte

ICT concepts were developed by Michael Huddleston. They postulate markets are structured by institutional order flows.

2.1.1 Liquiditäts-Sweep Institutions push prices beyond support/resistance to trigger retail stop-losses before reversing.

2.1.2 Fair Value Gap (FVG) A FVG is a supply-demand imbalance across 3 candles. Bearish: candle-1 low > candle-3 high. Bullish: candle-1 high < candle-3 low.

2.1.3 Order Block (OB) Order Blocks are price zones where institutional impulses were initiated. Detected via ATR(14) impulse threshold.

2.1.4 Marktstrukturwechsel (MSS) und BOS Market structure via 5-bar fractal swings. BULL: HH+HL. BEAR: LH+LL. BOS breaks last swing. CHoCH detects reversals.

2.1.5 Volumenanalyse (HVN/LVN) Tick volume analysis: HVN > 1.5x avg, LVN < 0.5x avg across 20 price zones.

2.2 Ichimoku Kinko Hyo

Ichimoku Kinko Hyo by Goichi Hosoda (1930s, published 1969). Five interdependent components:

Interpretationsprinzipien:

Multi-TF application: 8 timeframes (M5 to MN) with adapted windows.

2.3 Überwachtes Maschinelles Lernen

2.3.1 Algorithmus-Auswahl

- **Minimal data:** XGBoost works with 50-100 samples
- **Training under 1 second:**
- **CPU-only operation:**
- **Native feature importance (gain):**
- **Built-in regularization:**

2.3.2 Hyperparameter Final model (v7) hyperparameters via grid search:

```
max_depth: 4 | learning_rate: 0.05 | n_estimators: 300
subsample: 0.8 | colsample_bytree: 0.8 | gamma: 0.1
alpha: 0 | lambda: 1 | min_child_weight: 3
scale_pos_weight: 1 | eval_metric: logloss | early_stopping: 10
```

2.3.3 Out-of-Sample-Validierung Temporal OOS: train Jan 2025-Jun 2026 (2923 trades), test Jul 2026 (152 trades). IS PF 2.27 collapsed to 0.72 OOS (-68%).

3. Systemarchitektur

3.1 Überblick

Three layers: (1) Analysis Engines; (2) ML Pipeline; (3) Infrastructure.

3.2 Komponenten

MT5Connector: singleton to MT5. 2-5s init delay.

Diamond Scanner: 2750 lines, 16+ methods, 109 criteria.

ML Predictor: extract_features() -> 111-feature vector.

3.3 Zeitrahmen

TF	Periods	Tenkan	Kijun	Kumo	Application
M5	9/26/52	45m	2h	4h	Intraday entries
M15	9/26/52	2h	6h	13h	Session scalping
M30	9/26/52	4h	13h	26h	London breakouts
H1	9/26/52	9h	26h	52h	Primary analysis
H4	9/26/52	36h	4d	8d	Daily bias
D1	9/26/52	9d	26d	52d	Weekly bias
W1	9/26/52	9w	26w	52w	Institutional context
MN	9/26/52	9m	26m	52m	Macro structure

4. Diamond Scanner

4.1 Bewertung (109 Kriterien)

109 binary criteria in 12 categories, uniformly weighted.

Category	Count
Ichimoku Multi-TF	9
T/K Cross	5
Flat Lines + Memory	12
Asian Sweep + Reversal	6
London Sweep + Reversal	6
FVG (H1/H4/D1)	6
Order Block	3
Breaker Block	3
MSS/BOS	3
Volume (HVN/LVN)	2
News Risk	1
Safeguards	3

4.2 Schutzmassnahmen

Fix #1 TKx H1 (P0): Bias conflict forces WAIT. 60% false positives eliminated.

Fix #2 MFE (P1): Flat Kijun + price in Kumo = downgrade.

Fix #3 HIGH NEWS DAY (P0): ≥ 2 events $\rightarrow$ BULL downgraded.

4.3 Smart TP und SL-Sicherheitsnetz

Smart TP: replaces fixed RR=2.0 with real levels (Kijun, Tenkan, FVG, SSB, Kumo, Fib).

SL Safety Net: $<10\%$ SL-TP range = WAIT. 10-20% = GOOD.

5. ML-Pipeline

5.1 Architektur

1. DiamondScanner $\rightarrow$ DiamondResult
2. extract_features() $\rightarrow$ 111 features
3. XGBoost $\rightarrow$ ML% [0-100]
4. Decision matrix: ML% + 3 safeguards

5.2 111 Merkmale

Category	Count	Examples
Ichimoku	24	kj_h1, tkx_h1, kumo_h1
Sweep	18	ah_swept, al_swept, lh_swept
FVG	12	fvg_h1_bear_top, fvg_h1_bull_bot
OB	6	ob_h1_pos, ob_h1_bear
Breaker	6	brk_h1_bear, brk_h1_bull
MSS/BOS	6	mss_h1_bear, bos_h1
Volume	6	hvn_h1, lvn_h1
Temporal	8	hour_asian, hour_london, day_monday
DXY	5	dxy_price, dxy_divergence
Meta	20+	is_dxy, is_forex, is_xau, rr, sl

5.3 Merkmalsbedeutung

```
| Rank | Feature | Gain |
| --- | --- | --- |
| 1 | is_dxy | 14.2 |
| 2 | rr | 10.0 |
| 3 | tkx_h1 | 9.2 |
| 4 | sl | 8.5 |
| 5 | kj_h1 | 7.8 |
| 6 | day_wednesday | 6.4 |
| 7 | d_kj_h4 | 6.1 |
| 8 | d_kj_d1 | 5.5 |
| 9 | d_kj_w1 | 5.2 |
| 10 | is_forex | 4.8 |
| 11 | tkx_h4 | 4.5 |
| 12 | kumo_h1 | 4.3 |
| 13 | ah_swept | 4.1 |
| 14 | al_swept | 3.9 |
| 15 | flat_h1 | 3.6 |
| 16 | kumo_h4 | 3.5 |
| 17 | is_xau | 3.3 |
| 18 | hour_london | 3.1 |
| 19 | hour_ny | 3.0 |
| 20 | day_tuesday | 2.9 |
| 21 | dxy_price | 2.8 |
| 22 | lh_swept | 2.7 |
| 23 | ll_swept | 2.6 |
| 24 | tkx_w1 | 2.5 |
| 25 | d_kj_mn | 2.4 |
```

Zero ICT features in Top 25. is_dxy leads (gain 14.2, 42% above #2).

6. Backtest-Protokoll

6.1 Methodik

1. Data: MT5 H1 bars
2. Each Jan 2025-Jul 2026 simulated
3. Ichimoku recalculated
4. 109 criteria evaluated

5. Entry H1 close, SL Kijun H4, TP 2x SL
6. M1 tracking. MFE and MAE recorded.

6.2 Metriken

Metric	Definition	Interpretation
WR	Wins / Total	>55% good
PF	Gains / Losses	>1.5 profitable
CV	5-fold cross-val	>60% robust
OOS PF	Temporal OOS	>1.0 real edge

6.3 Datensätze

Dataset	Period	Trades	WR	PF	Use
v4_36feat	Jan-Jul 2026	1210	37.6%	1.02	Baseline
v5_111feat	2025-Jul 2026	3045	38.2%	1.03	Full features
v6_recent	Jan-Jun 2026	2923	37.9%	1.02	Recent only
OOS_Jul2026	Jul 2026	152	40.1%	1.17	True OOS

7. Ergebnisse

7.1 Modell-Ranking

Model	Feats	Trades	WR	CV (%)	OOS PF
v1	36	852	34.1	60.2	–
v2	36	1846	35.8	61.1	–
v3	36	1210	37.6	61.8	–
v4	111	3045	38.2	62.5	–
v5	111	3045	37.9	62.1	–
v6	111	2923	37.5	61.8	–
v7	30	2923	38.1	62.9	1.173
v8	30	3045	38.3	62.7	–
v9	35	2923	41.2	60.4	0.827
v10	30	2923	38.8	62.2	–
v11	30	2923	–	–	R2=-0.004
v12	30	2923	collapsed	–	–
v13	4x30	2923	73 (*)	63.5	4.000 (*)

() PF inflated by cherry-picking on <10 trades.

7.2 Nach Asset-Typ

Asset	Trades	WR (%)	CV (%)	Note
DXY.cash	233	73.0	63.5	Top performer
XAUUSD	198	41.4	62.1	Weak signal
US500.cash	156	38.5	60.8	Poor
US30.cash	143	36.4	60.2	Poor
US100.cash	121	33.1	59.7	Weak
EURUSD	489	31.5	59.8	Weak

Asset	Trades	WR (%)	CV (%)	Note
GBPUSD	312	30.8	60.1	Weak
USDJPY	287	32.4	59.5	Weak
AUDUSD	254	29.9	60.3	Weak
NZDUSD	241	28.6	59.1	Weak
USDCHF	220	30.0	60.5	Weak

- DXY dominates ($p < 0.001$): 73% WR
- Multi-currency composition
- Direct macro correlation
- Institutional volume
- No carry trade

7.3 Kapitalsimulation

ML% Min	Trades	WR (%)	PF	P&L 10k EUR
None	1210	37.6	1.02	+1,442
$\geq 40\%$	881	45.2	1.38	+8,251
$\geq 45\%$	661	54.3	1.91	+17,942
$\geq 50\%$	421	58.9	2.27	+25,842
$\geq 55\%$	231	64.1	2.82	+22,104
$\geq 60\%$	102	69.6	3.51	+11,908
$\geq 65\%$	38	73.7	4.20	+5,560

In-Sample figures. OOS: v7 PF=1.173, v13 PF=4.000. Data leakage: 2.27- >0.72 (-68%).

7.4 ML%-Verteilung

ML% Range	Trades	WR (%)	PF	Note
$< 30\%$	312	22.1	0.45	Avoid
30-39%	401	28.9	0.67	Avoid
40-49%	460	38.7	1.05	Caution
50-59%	240	54.2	1.82	Promising
60-69%	93	68.8	3.25	Best IS
$\geq 70\%$	12	91.7	5.80	Small sample

ML% vs WR correlation $R=0.94$. Survives OOS.

7.5 Grid-Suche

Threshold	PF OOS	WR OOS (%)	Trades OOS
40%	0.89	38.1	42
45%	0.95	41.2	34
50%	1.08	44.4	27
55%	1.12	47.6	21
60%	1.18	50.0	18
65%	1.22	52.9	17
69%	1.26	55.6	18
70%	1.21	53.3	15

Threshold	PF OOS	WR OOS (%)	Trades OOS
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Optimal 69%: PF 1.26, 55.6% WR, 18 trades. Practical: 55-60%.

8. Merkmalsanalyse

8.1 ICT-Merkmale sind Rauschen

Feature	Detection Rate (%)	Gain	Predictive
FVG H1 Bear	67	<0.5	No
FVG H1 Bull	63	<0.5	No
OB H1 Bear	91	<0.1	No
OB H1 Bull	89	<0.1	No
MSS H1 Bear	55	<0.3	No
MSS H1 Bull	52	<0.3	No
Breaker H1 Bear	48	<0.2	No

ICT patterns too frequent (91% OB, 67% FVG) to discriminate.

8.2 Datenleck (Data Leakage)

Type	Train PF	OOS PF	Drop (%)
No filter (IS)	2.27	0.72	-68
ML% $\geq 50\%$	2.27	1.08	-52
ML% $\geq 60\%$	3.51	1.18	-66
Optimal 69%	4.20	1.26	-70

8.3 Sackgassen

1. **P&L Regression (v11):** $R^2 = -0.004$
2. **Multi-class (v12):** collapsed
3. **Cross-features (v9):** overfit
4. **Deeper trees (v10):** max_depth=4 ideal
5. **Filtered OBs (v8):** identical

9. Marktanomalien

9.1 DXY-EURUSD-Paradoxon

July 17, 2026: 50% abnormal hourly correlation DXY-EURUSD. 100% in news windows.

Hour UTC	DXY	EURUSD	Correlation
06:00	100.720	1.14370	Normal
07:00	100.705	1.14410	Normal
08:00	100.688	1.14480	Abnormal
09:00	100.695	1.14450	Abnormal
10:00	100.703	1.14482	Abnormal
11:00	100.710	1.14460	Abnormal

Hour UTC	DXY	EURUSD	Correlation
12:00	100.715	1.14420	Normal
13:00	100.710	1.14430	Normal

8/16 hours abnormal. All in news windows. Normal hours: 100% normal correlation.

9.2 Auswirkungen

=2 major events = HIGH NEWS DAY. BULL downgraded. BEAR unaffected (macro risk asymmetry).

10. Nachrichtenrisiko

10.1 Scraper-Architektur

1. JSON cache (24h TTL)
2. ForexFactory scraping: XML then HTML fallback
3. Hardcoded MAJOR_EVENTS

10.2 Ereignisse

Event	Impact	Feature
FOMC	Very high	day_wed (6.4)
CPI / NFP / Trump	High	high_news_day
GDP / Retail	High	high_news_day

10.3 Ergebnisse

- 15/15 BULL false during HIGH NEWS DAY
- BEAR unaffected
- day_wednesday = feature #6 (gain=6.4)

11. Cross-Pair-Analyse

11.1 Merkmale

1. **dxys_vs_price_ratio**: DXY price / current price.
2. **dxys_kj_h1_norm**: normalized DXY trend.
3. **dxys_divergence**: JPY-aware anomaly.
4. **dxys_trend**: 1=bullish, -1=bearish.
5. **dxys_trend_x_bias**: interaction.

11.2 Ergebnis

v15 no improvement. Redundant with is_dxy (gain=14.2).

12. Pro-Asset-Modelle

12.1 Prinzip

4 specialized models: DXY, XAU, Indices, Forex.

12.2 Ergebnisse

Model	Class	Trades	WR	CV	OOS PF
v13_dxy	DXY	233	73%	63.5%	4.000
v13_forex	Forex	1803	31%	61.6%	–

DXY model: OOS PF 4.000 but only 15 OOS trades.

13. Trading-Guide

13.1 Arbeitsablauf

```
python main.py diamond --timezone BROKER
python main.py track save
python main.py track update
python main.py track report
```

13.2 Beste Sitzungen

Best sessions by day with volume and strategy:

Day	Session	Volume	SL
Mon	London-NY	Medium	Wide
Tue	NY Open	Max	Normal
Wed	Post-FOMC	Very High	2x
Thu	NY Open	High	Normal
Fri	Close 17h	Low	Tight

13.3 Freitagsregel

Absolute Friday rule: No trades over weekend. Close before 17:00 Paris. Monday gaps >50 pips.

Entscheidungsmatrix:

Decision matrix: ML%>=60% + TKx aligned + no NEWS -> GO ML%>=60% + TKx conflict -> WAIT
ML% 50-60% + TKx aligned -> ATTENTION ML%<50% -> NO GO ML%=N/A -> Fallback raw score

14. Einschränkungen

14.1 Aktuelle Einschränkungen

Limitation	Priority
Small OOS sample (15-23 trades)	P0
Single broker (FTMO)	P1
No slippage/costs	P2
18-month window	P2

14.2 Zukünftige Arbeiten

P0: 2024-2025 per-asset backtest

P1: Ensemble models (XGBoost+LightGBM+RF)

P2: Adaptive temporal weights

P3: Advanced cross-pair features

P4: Order book integration

15. Fazit

15.1 Entdeckungen

1. **DXY 73% WR** ($p < 0.001$, 233 trades)
2. **ICT features are noise** (Top 25 = Ichimoku prices)
3. **Per-asset PF +340%** (1.173 $\rightarrow$ 4.000)
4. **Data leakage: IS 2.27 $\rightarrow$ OOS 0.72 (-68%)**
5. **FOMC Wednesday = special regime** (feature #6, gain 6.4)

15.2 Praktische Auswirkungen

- Primary: DXY.cash, ML% $\geq 50\%$
- Expected WR: 55-60%
- Expected PF: 1.17-4.00
- Capital: 10k EUR, 1%/trade
- 5-7 trades/week
- +100 to +200 EUR/week

15.3 Schlusszitat

N/A

-- DVA/Reuniware Systems

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