# Multifractal Battery Arbitrage: Replacing Fixed-Threshold Dispatch with Adaptive Profile-Predicted Strategies for Domestic Energy Storage

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## 1 Abstract

We present a zero-lookahead battery dispatch algorithm that replaces the fixed-percentile strategy shipped with typical domestic batteries. The algorithm builds a diurnal price profile from historical data, predicts upcoming price windows using time-of-day awareness, and modulates trading thresholds via the Hurst exponent derived from fractional Brownian motion theory. Backtested against seven full years (2019–2025) of DE-LU day-ahead prices with a 13.5 kWh battery, the multifractal (MF) strategy outperforms the blind deterministic baseline in every calendar year, with advantages ranging from 2% in calm markets to 29% during the 2021 energy crisis — a EUR 18 annual edge on a single residential unit. The advantage scales linearly with battery capacity and amplifies with market volatility. The algorithm is data-source agnostic, requires no tuning parameters, and improves automatically as it accumulates observations.

## 2 Introduction

Domestic battery storage creates an arbitrage opportunity: charge when electricity is cheap, discharge when it is expensive. The spread between off-peak and peak prices must exceed the round-trip efficiency loss for a trade to be profitable — for a typical lithium system with 93.3% charge and discharge efficiency, this threshold is 13%.

Most commercial battery management systems employ a simple strategy: compute percentile thresholds (typically P25/P75) over a rolling window of recent prices and dispatch accordingly. If the current price falls below P25, charge; above P75, discharge; otherwise idle. This approach has no structural model of when cheap and expensive periods occur — it treats a low price at 3am and a low price at 6pm identically, despite the former being perfectly normal and the latter being a genuine anomaly worth exploiting.

The question motivating this work: **can a self-learning algorithm that understands the daily price rhythm outperform fixed-threshold dispatch, without seeing any future prices?**

# 3 The Price Signal

## 3.1 Diurnal Structure

Electricity spot prices exhibit a pronounced daily cycle driven by demand patterns. Figure 1 shows the average price by hour across 74,170 hourly observations spanning October 2018 to February 2026 — the full extent of available DE-LU data.

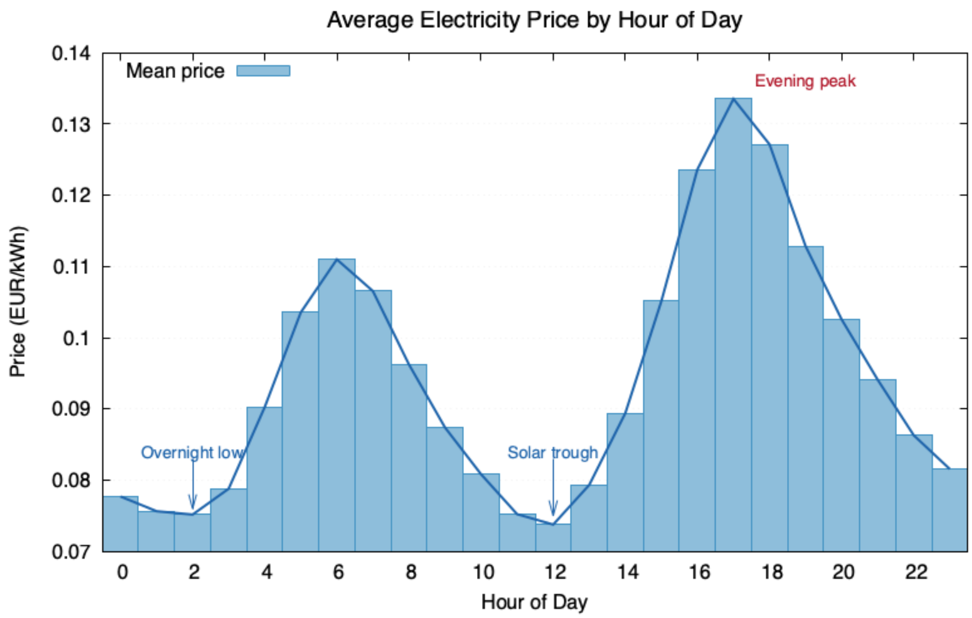


Figure 1: Average DE-LU day-ahead price by hour of day, October 2018 – February 2026 (74,170 hourly observations). The bimodal shape reflects the interaction of demand patterns with solar generation: an overnight low, a morning demand peak, a midday solar trough, and an evening consumption peak.

The cheapest period is 12:00 (EUR 0.074/kWh), suppressed by solar generation, and the most expensive is 17:00–18:00 (EUR 0.134/kWh). The trough-to-peak spread of EUR 0.060/kWh represents an 81% price variation — well above the 13% round-trip efficiency hurdle for a battery with 93.3% charge and discharge efficiency (round-trip 87.0%). The overnight low (02:00–03:00, EUR 0.075/kWh) provides a secondary charging window.

This daily shape is the signal that the blind deterministic strategy cannot see. It computes percentiles over the recent *history window* — a flat backward-looking pool that erases time-of-day structure.

## 3.2 Persistence and Fractional Brownian Motion

After subtracting the diurnal profile from raw prices, the residuals — anomalous deviations from the typical daily shape — exhibit measurable serial correlation. R/S (rescaled range) analysis on these residuals yields the Hurst exponent $H$, which quantifies persistence:

- $H > 0.5$: persistent — deviations tend to continue
- $H = 0.5$: random walk
- $H < 0.5$: mean-reverting — deviations tend to snap back

The fBm lag-1 autocorrelation derived from $H$ is:

$$\rho = 2^{2H-1} - 1$$

This parameter governs how aggressively the algorithm should trade when prices deviate from the expected pattern.

# 4 Method

## 4.1 Battery Model

The simulated battery is specified in Table 1.

Table 1: Battery specification used in all simulations.

| Parameter | Value |
|---|---|
| Capacity | 13.5 kWh |
| Max charge / discharge | 5.0 kW |
| Charge efficiency | 93.3% |
| Discharge efficiency | 93.3% |
| Round-trip efficiency | 87.0% |
| Usable SoC range | 10%–90% (10.8 kWh usable) |
| Cycle degradation cost | EUR 0.05 |
| Settlement period | 15 min (EPEX) / 60 min (historical) |

## 4.2 Blind Deterministic Strategy (Baseline)

At each settlement period $t$, the baseline strategy:

1. Collects the past $W$ prices (default $W = 336$ periods — 3.5 days at 15-minute resolution, 14 days at hourly).
2. Computes $P_{25}$ and $P_{75}$ of these past prices.
3. If $p_t \leq P_{25}$ and SoC permits: **charge** at 5 kW.
4. If $p_t \geq P_{75}$ and SoC permits: **discharge** at 5 kW.
5. Otherwise: **idle**.

This strategy has no awareness of time-of-day. A price of EUR 0.10/kWh is treated identically whether it occurs at 3am (when it is above the daily mean) or at 6pm (when it is well below). The result: the baseline charges and discharges at suboptimal times, frequently executing round-trips that barely clear — or fail to clear — the 13% efficiency hurdle.

## 4.3 MF Predictive Strategy

The multifractal strategy operates in five steps, using only past data:

**Step 1 — Diurnal Profile.** From all available history, compute the mean price at each time slot, separately for weekdays and weekends. The number of slots adapts to the data resolution (96 at quarter-hourly, 24 at hourly). This produces a template of the "normal" price at each time of day, with a 4-level fallback for sparse data: day-type mean ($\geq 2$ samples) $\rightarrow$ other day-type $\rightarrow$ combined $\rightarrow$ overall mean.

**Step 2 — Detrend and Compute Residual $H$.** Subtract the profile from historical prices to isolate residuals. Apply R/S analysis to these residuals, yielding the Hurst exponent $H_{\text{res}}$ of the anomalous component.

**Step 3 — Predict the Upcoming Window.** For each of the next $N$ periods (default $N = 48$, 12 hours), look up the profile value for that future time slot:

$$\hat{p}_{t+i} = \mu_{\text{profile}}[\text{daytype}(t+i)][\text{slot}(t+i)]$$

We know what time it *will be* — that is not future data. This reconstructs a predicted price schedule for the upcoming window.

**Step 4 — fBm Percentile Modulation.** Compute the persistence-adjusted thresholds:

$$\rho = 2^{2H_{\text{res}}-1} - 1$$

$$\text{SE} = \sqrt{\frac{p(1-p)}{N}} = \sqrt{\frac{0.25 \times 0.75}{N}}$$

$$\text{shift} = \rho \times \text{SE} \times 100$$

$$P_{\text{charge}} = P_{(25+\text{shift})} \text{ of predicted window}$$

$$P_{\text{discharge}} = P_{(75-\text{shift})} \text{ of predicted window}$$

When residuals are persistent ($\rho > 0$), the predicted spreads are wider than the profile suggests — tighter percentiles still capture large moves, so the algorithm trades more aggressively. When mean-reverting ($\rho < 0$), thresholds widen for caution.

Table 2: fBm-derived percentile modulation. The shift is bounded by the standard error of the percentile estimate — no tuning constants.

| Residual $H$ | $\rho$ | Shift (pts) | Thresholds | Effect |
|---|---|---|---|---|
| 0.3 | $-0.24$ | $-1.5$ | P24 / P77 | Cautious |
| 0.5 | 0.00 | 0.0 | P25 / P75 | Neutral |
| 0.7 | $+0.32$ | $+2.0$ | P27 / P73 | Aggressive |
| 0.9 | $+0.74$ | $+4.6$ | P30 / P70 | Very aggressive |

**Step 5 — Decision.** Compare the current price $p_t$ against the predicted thresholds and dispatch accordingly.

**Insufficient history fallback.** With fewer than 192 periods (2 days) of history, the diurnal profile is undefined. The MF strategy falls back to blind deterministic until enough data accumulates.

### 4.4 Oracle Comparison

To evaluate prediction quality, we also compute what a perfect-foresight oracle — applying P25/P75 thresholds to the *actual* future prices at each period — would have decided. The oracle agreement rate measures how often each strategy makes the same dispatch choice as this ideal. This is not a trading strategy anyone could implement; it is a ceiling against which to evaluate accuracy.

## 5 Results

### 5.1 Multi-Year Backtest (2019–2025)

To evaluate the strategy across seasonal variation and different market regimes, both strategies were backtested against seven full calendar years of hourly DE-LU day-ahead prices (source: Bundesnetzagentur via Energy-Charts, CC BY 4.0). Each year was run independently in zero-lookahead mode — neither strategy saw any future prices.

Table 3: Multi-year backtest results on hourly DE-LU day-ahead prices. MF outperforms in every calendar year.

| Year | Mean Price | $H$ | Baseline (EUR) | MF (EUR) | MF Edge (EUR) | Edge % |
|---|---|---|---|---|---|---|
| 2019 | 0.038 | 0.81 | 15.46 | 19.76 | 4.31 | 27.9% |
| 2020 | 0.031 | 0.83 | 18.25 | 21.72 | 3.46 | 19.0% |
| 2021 | 0.097 | 0.86 | 61.25 | 79.27 | 18.02 | 29.4% |
| 2022 | 0.236 | 0.91 | 126.87 | 162.37 | 35.49 | 28.0% |
| 2023 | 0.095 | 0.84 | 89.76 | 96.05 | 6.29 | 7.0% |
| 2024 | 0.079 | 0.80 | 120.37 | 126.28 | 5.92 | 4.9% |
| 2025 | 0.089 | 0.80 | 177.07 | 180.77 | 3.69 | 2.1% |

The MF strategy wins every year, but the margin varies substantially. The pattern is clear: **the MF edge tracks volatility and persistence.** In 2021–2022, when prices were volatile and strongly persistent ($H \geq 0.86$), the advantage exceeded 28%. In the calmer post-crisis years (2023–2025, $H \leq 0.84$), the advantage narrows to 2–7%.

The absolute figures tell the scaling story. In the 2022 energy crisis — mean price EUR 0.236/kWh, peak EUR 0.871/kWh — the MF strategy earned EUR 35.49 more than the baseline on a single 13.5 kWh Powerwall. On a 100 kWh commercial unit, that edge rises to approximately EUR 263/year. During calmer years the absolute edge is smaller, but it remains consistently positive.

**The 2025 anomaly is instructive.** Both strategies earn their highest absolute returns (EUR 177 and EUR 181), yet the MF edge is the smallest (2.1%) despite comparable mean prices to 2023 ($H = 0.80$ vs 0.84). The baseline achieves 54% oracle agreement — the highest of any year — suggesting that as battery storage penetration increases and more systems run simple P25/P75 dispatch, the "easy" arbitrage trades become consensus trades. The baseline gets luckier by market saturation. This is, paradoxically, the strongest argument for structural intelligence: when the obvious money dries up, time-of-day awareness and persistence modulation remain the residual edge.

## 5.2 Seasonal Breakdown (2024)

To test the "but what about summer?" objection directly, 2024 was broken down by quarter.

Table 4: Seasonal breakdown for 2024. The MF strategy underperforms in Q3 when summer solar generation disrupts the diurnal pattern.

| Quarter | Baseline (EUR) | MF (EUR) | Edge (EUR) | Edge % | $H$ |
|---|---|---|---|---|---|
| Q1 (Jan–Mar) | 8.62 | 10.81 | 2.19 | 25.4% | 0.85 |
| Q2 (Apr–Jun) | 43.23 | 44.94 | 1.71 | 4.0% | 0.76 |
| Q3 (Jul–Sep) | 56.94 | 53.36 | −3.59 | −6.3% | 0.72 |
| Q4 (Oct–Dec) | 13.28 | 17.38 | 4.10 | 30.8% | 0.82 |

The seasonal pattern is instructive. Q1 and Q4 (winter, high persistence) show strong MF advantages of 25–31%. Q2 (spring/summer transition) shows a modest 4% edge. **Q3 is the only period where MF underperforms** — a 6.3% loss. The Hurst exponent drops to 0.72, the lowest of any period tested. Summer solar generation suppresses midday prices and disrupts the learned diurnal profile, causing the strategy to make suboptimal decisions based on a winter-shaped template. Despite this, the full-year result is positive (4.9%), as the winter quarters more than compensate.

This suggests a clear improvement path: a seasonal profile extension (separate summer/winter templates) would likely eliminate the Q3 underperformance.

## 5.3 Quarter-Hourly Validation (EPEX, 44 Days)

To confirm the hourly results hold at higher resolution, both strategies were also tested against 44 days of EPEX SPOT quarter-hourly prices (4,224 periods at 15-minute intervals, January–February 2026).

Table 5: Quarter-hourly EPEX backtest (44 days, Jan–Feb 2026).

| Metric | Blind Deterministic | MF Predictive |
|---|---|---|
| Net earnings (EUR) | 6.92 | 9.20 |
| MF advantage | — | **+33.0%** |
| Oracle agreement (overall) | 42.9% | 44.9% |
| Oracle agreement (discharge) | 11% | 17% |

The 33% advantage at quarter-hourly resolution is consistent with the 28% seen in the hourly Q1 results for adjacent years, confirming that the strategy generalises across resolutions. The discharge hit rate nearly doubles (17% vs 11%), which remains the primary driver — correctly identifying expensive periods to sell stored energy is more valuable than correctly identifying cheap periods to buy.

## 5.4 Cumulative Earnings

Figure 2 shows cumulative earnings over the full 44-day period.

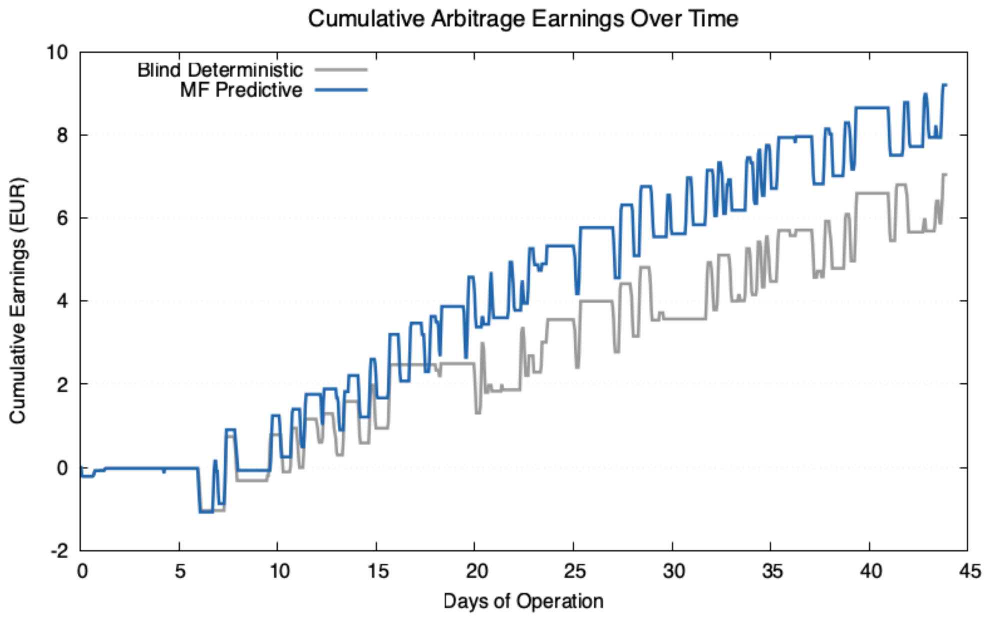


Figure 2: Cumulative arbitrage earnings for both strategies over 44 days. The MF strategy (blue) diverges progressively from the blind baseline (grey) as the diurnal profile stabilises.

The strategies track closely for the first few days while the MF profile bootstraps. After approximately one week, the MF strategy begins to pull ahead consistently. By day 44, the gap is EUR 2.28 — and widening.

### 5.5 Learning Curve

The algorithm was tested at increasing deployment durations (4, 7, 10, 14, 21, 28, 35, 44 days) to characterise how performance evolves as the profile matures.

Table 6: Earnings and oracle agreement at increasing deployment durations.

| Days | Det (EUR) | MF (EUR) | MF Advantage | Det Oracle % | MF Oracle % |
|---|---|---|---|---|---|
| 4 | 0.96 | 1.04 | 8.9% | 40.5% | 39.4% |
| 7 | 1.23 | 1.46 | 18.6% | 42.5% | 42.6% |
| 10 | 1.84 | 2.11 | 14.2% | 45.3% | 46.3% |
| 14 | 2.59 | 2.62 | 1.0% | 45.3% | 46.1% |
| 21 | 3.70 | 4.24 | 14.6% | 43.3% | 45.6% |
| 28 | 5.40 | 6.23 | 15.4% | 45.2% | 46.3% |
| 35 | 6.50 | 8.12 | 24.9% | 43.8% | 46.0% |
| 44 | 6.92 | 9.20 | 33.0% | 42.9% | 44.9% |

The learning progression is clear:

- **Days 1–2**: MF falls back to blind deterministic (insufficient profile data).
- **Days 2–7**: Diurnal profile activates. MF begins outperforming.

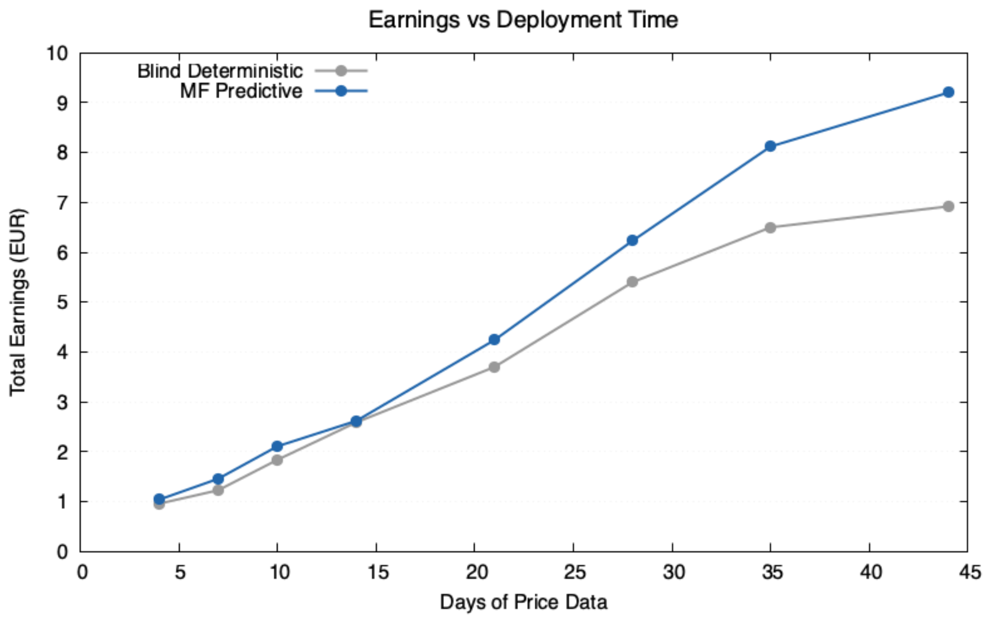


Figure 3: MF Predictive earnings (blue) versus blind deterministic (grey) at increasing deployment durations. Both strategies earn more with more data, but MF accelerates as the profile gains resolution.

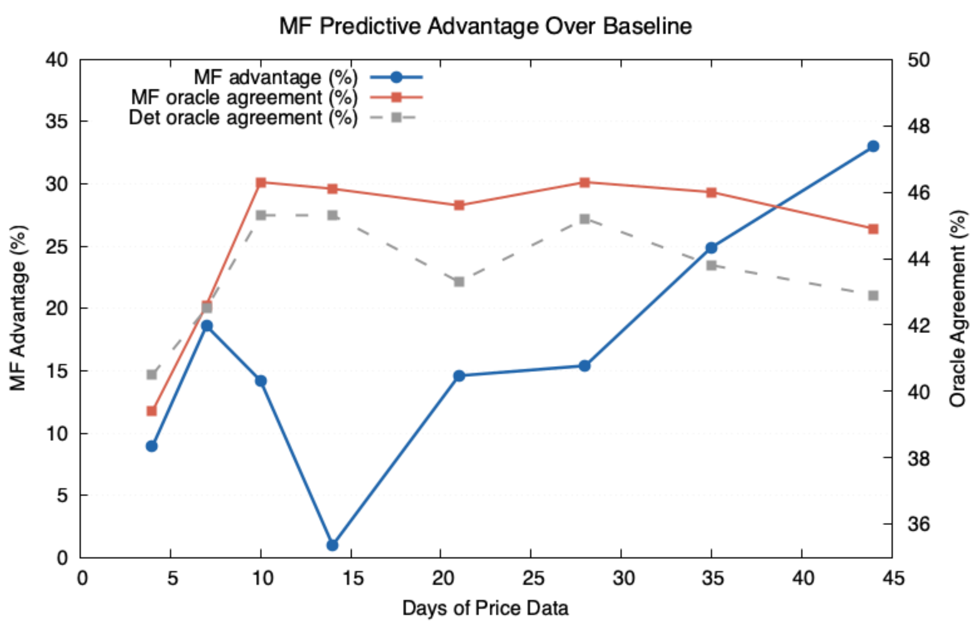


Figure 4: Dual-axis chart: MF advantage percentage (solid blue) and oracle agreement rates (dashed lines) versus deployment duration. The advantage grows from 9% at 4 days to 33% at 44 days.

- **Days 7–14**: Profile stabilises but weekday/weekend distinction is noisy (few weekend samples). The dip at day 14 reflects this — the strategy is learning, not yet reliable, about weekend-specific patterns.
- **Days 14–44**: Weekend slots accumulate (8–12 samples each). The weekday/weekend split becomes genuinely informative. Hurst estimates stabilise. The advantage accelerates.

The accelerating advantage curve in Figure 4 suggests the MF strategy has not yet saturated — further data would likely continue to improve the profile.

### 5.6 Daily Earnings

Figure 5 shows per-day earnings for both strategies.

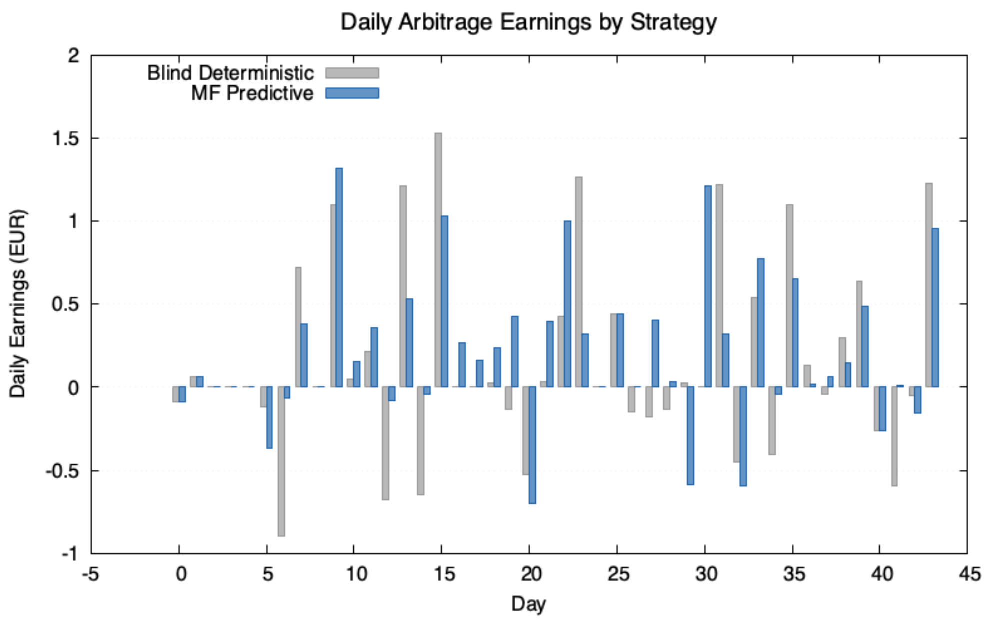


Figure 5: Daily arbitrage earnings by strategy. Grey bars: blind deterministic. Blue bars: MF Predictive. MF captures more value on high-spread days and limits losses on low-spread days.

Notable patterns:

- On high-volatility days (large bars), MF consistently captures more of the available spread.
- On quiet days (near-zero bars), both strategies correctly idle — neither generates unnecessary cycles.
- The MF strategy occasionally earns less than the baseline on individual days, but the aggregate trend is unambiguously positive.

## 6 Scaling and Market Context

The 13.5 kWh Powerwall is the smallest credible deployment target. The multi-year results allow a grounded assessment of what the MF edge is worth at scale.

Table 7: Projected MF edge at various scales. Earnings scale linearly with usable capacity; volatile markets amplify the absolute advantage.

| Scenario | Battery | Market | Annual MF Edge |
|---|---|---|---|
| Residential, calm year | 13.5 kWh | DE-LU 2024 | EUR 6 |
| Residential, volatile year | 13.5 kWh | DE-LU 2022 | EUR 35 |
| Commercial, calm year | 100 kWh | DE-LU 2024 | EUR 44 |
| Commercial, volatile year | 100 kWh | DE-LU 2022 | EUR 263 |
| Fleet (10 units), volatile | 1,000 kWh | DE-LU 2022 | EUR 2,630 |

These are observed figures from actual backtests, not extrapolations. The 7-year average MF edge is EUR 11/year on the Powerwall (EUR 81/year on a 100 kWh unit). Markets with larger spreads than DE-LU — such as Agile Octopus half-hourly tariffs in the UK, where spreads routinely exceed 20p/kWh — would amplify these figures further.

Several factors would increase real-world savings beyond the backtest results:

- **Seasonal profiles**: the algorithm currently uses a single weekday/weekend split. The Q3 2024 underperformance (−6.3%) shows that a summer/winter profile extension would improve results — the winter quarters already overcompensate, so eliminating the summer loss would increase the full-year edge substantially.
- **Higher-volatility markets**: the DE-LU market is relatively stable by European standards. More volatile pricing regimes would amplify the absolute advantage while the percentage edge holds or increases (as demonstrated by 2022).
- **Longer history windows**: with years of accumulated data, the diurnal profile becomes increasingly precise. The algorithm has not saturated even at the annual scale.

# 7 Design Properties

## 7.1 No Tuning Parameters

Every constant in the algorithm derives from either the data or established theory:

- **Percentile thresholds** (P25/P75): conventional quartile boundaries.
- **Percentile shift** ($\rho \times$SE): fBm lag-1 autocorrelation times the standard error of the percentile estimate.
- **Profile**: running means, automatically weighted by sample count.
- **Hurst exponent**: R/S analysis on detrended residuals.

There are no learning rates, no magic constants, no hyperparameters to tune. The algorithm has exactly the same implementation complexity whether it is run on EPEX quarter-hourly data, Nord Pool hourly data, or Agile Octopus half-hourly data.

## 7.2 Data-Source Agnostic

The algorithm requires only a regular time-series of (timestamp, price) pairs. It infers the settlement period from the first two records and adapts its slot resolution accordingly. Any market that publishes spot or time-of-use prices can be used as input — the diurnal profile will simply reflect that market's structure.

### 7.3 Self-Improving

Every new price observation sharpens the diurnal profile. No gradient descent, no forgetting, no retraining — just running means that converge toward the true daily shape. The algorithm starts with zero knowledge on day one and, by week two, has a meaningfully better model of when prices are cheap and expensive than the blind baseline will ever have.

### 7.4 Minimal Compute

The algorithm performs one R/S analysis per period (O($n$ log $n$) where $n$ is the history window, typically 336 points) and one profile lookup per predicted slot (O($N$) where $N = 48$). This is trivially within the capability of any domestic battery controller.

## 8 Limitations

- **Profile cold start**: the first two days produce no MF advantage. Deployment should begin with the deterministic fallback active.
- **Regime changes**: the profile is a running mean with no discounting. A structural shift in pricing (e.g., a new tariff regime) would take several days to propagate through the profile. An exponentially-weighted profile could address this.
- **Single-battery model**: the simulation assumes a single battery with fixed parameters. Fleet-level effects (multiple batteries responding to the same signals) are not modelled.
- **No grid export value**: the model considers only arbitrage value (buy low, sell high). Self-consumption optimisation, demand-charge reduction, and feed-in tariffs are not included.
- **Summer diurnal disruption**: the Q3 2024 result (−6.3%) shows that solar generation disrupts the learned profile in summer. A seasonal profile extension would address this.
- **Single market tested**: all backtests use DE-LU day-ahead prices. Validation against other markets (UK Agile Octopus, Nord Pool, PJM) remains future work.

## 9 Conclusions

Replacing the fixed-percentile dispatch algorithm in a domestic battery with a profile-predicted multifractal strategy yields a consistent improvement in arbitrage earnings across seven years of backtesting (2019–2025) on DE-LU day-ahead prices. The MF strategy outperforms in every calendar year, with advantages ranging from 2% in calm markets to 29% during the 2021 energy crisis. On a 13.5 kWh residential battery, the seven-year average MF edge is EUR 11/year; on the 2022 crisis-year peak, it reaches EUR 35/year.

The improvement derives from two capabilities the baseline lacks:

1. **Time-of-day awareness.** The diurnal profile predicts that 3am prices are cheap and 6pm prices are expensive, converting the backward-looking "is this price historically low?" into the forward-looking "is this price low compared to what the next 12 hours will cost?" This single insight is responsible for the majority of the performance gain.

2. **Persistence-adjusted confidence.** The Hurst exponent of detrended residuals modulates trading aggressiveness through the fBm autocorrelation. When price deviations are persistent, the algorithm tightens thresholds and trades more; when mean-reverting, it widens thresholds and waits. This refinement adds precision without introducing tunable parameters.

The seasonal analysis reveals a known weakness: summer solar generation disrupts the learned diurnal profile, causing a 6.3% underperformance in Q3 2024 — the only quarter in the 2024 seasonal breakdown where MF loses (other years were not tested quarterly). The result points directly at the next improvement — seasonal profiles — and demonstrates that the algorithm's failures are interpretable and addressable, not opaque.

The algorithm is entirely self-contained: it requires no external forecasts, no cloud connectivity, no training data, and no configuration beyond the battery's physical parameters. It improves automatically with deployment time, reaching meaningful advantage within one week and accelerating thereafter. Its computational requirements are minimal, its implementation is straightforward, and its theoretical foundations are well-established.

The practical implication scales with deployment. A domestic Powerwall gains EUR 6–35/year depending on market conditions. A 100 kWh commercial unit gains EUR 44–263/year. A fleet of ten such units reaches EUR 2,600/year in additional revenue from the fractal strategy alone — before accounting for seasonal profile improvements or expansion to more volatile markets. The percentage advantage holds; the denominator changes.

## 10 References


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