# Decoding Market Vibration: A Functional Wave Analysis of Bitcoin Price Action

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December 30, 2025

**Abstract**

Standard financial analysis often treats market movements as stochastic processes or reactions to external news. This study proposes an alternative framework based on "Functional Wave Theory," positing that markets behave as energetic systems that accumulate vibrational charge before discharging into price volatility. By applying a sliding-window Fast Fourier Transform (FFT) to hourly Bitcoin (BTC-USD) data, we decompose price action into its constituent spectral energies. Furthermore, we separate these energies into low-frequency bands (attributed to retail sentiment) and high-frequency bands (attributed to algorithmic/institutional intent). The results demonstrate that periods of high accumulated spectral energy reliably precede major volatility events, and that diverging activity between high and low-frequency actors offers predictive insight into market accumulation and distribution phases.

# 1 Introduction

The underlying mechanics of market volatility remain one of the central challenges of financial engineering. While traditional models focus on moving averages and oscillator indicators derived from price, alternative physics-based viewpoints suggest looking at the "energy" driving the price, rather than the price itself.

Drawing inspiration from early 20th-century functional biophysics, we hypothesize that complex systems, including financial markets, operate via a pulsation principle: tension (charge accumulation) leads to discharge (price movement). In this context, "quiet" markets are not necessarily stable; they may be accumulating potential energy in the form of hidden frequency vibrations.

This experiment aims to validate two core hypotheses:

1. That total spectral energy (the sum of market vibration) serves as a leading indicator for volatility breakdowns.
2. That different market actors operate at distinct frequencies, allowing us to separate "informed" algorithmic trading (high frequency) from emotional retail trading (low frequency).

# 2 Methodology

## 2.1 Data Acquisition and Preprocessing

Historical price data for Bitcoin against the US Dollar (BTC-USD) was acquired via the `yfinance` API. To capture the necessary granularity for high-frequency actor detection, hourly interval data ('1h') over a one-year period was selected.

The raw closing prices ($P_t$) were converted into logarithmic returns ($R_t$) to normalize the dataset and focus specifically on volatility dynamics rather than absolute price trends:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

## 2.2 Spectral Energy Decomposition (FFT)

To detect hidden periodicities within the returns, a sliding-window Fast Fourier Transform (FFT) was employed. A window size of 48 hours was chosen to capture a full two-day trade cycle. A Hanning window function was applied to each segment to minimize spectral leakage at the boundaries.

The FFT converts the time-domain return data into the frequency domain, revealing the amplitude of various oscillatory components hidden within the market noise.

## 2.3 Frequency Band Separation

A crucial innovation of this methodology is the segregation of the frequency spectrum based on the presumed time horizons of different market actors:

- **Low-Frequency Energy (Retail Sentiment):** Defined as FFT bin indices 1 through 4. These represent slow, multi-hour to daily oscillations, characteristic of emotionally driven retail buying and selling pressure.
- **High-Frequency Energy (Algorithmic/Whale Intent):** Defined as FFT bin indices 10 through 20. These represent rapid oscillations occurring within 2 to 4-hour sub-cycles, characteristic of automated algorithmic execution and large-scale institutional positioning that cannot be sustained by manual trading.

# 3 Results and Discussion

## 3.1 Total Volatility Potential (The "Discharge" Threshold)

The initial analysis focused on the total accumulated spectral energy regardless of frequency band. This serves as a measure of overall system "anxiety" or vibration.

As presented in Figure 1, a clear threshold behavior emerges. The red dashed line represents a statistical danger zone (1.5 standard deviations above mean energy).

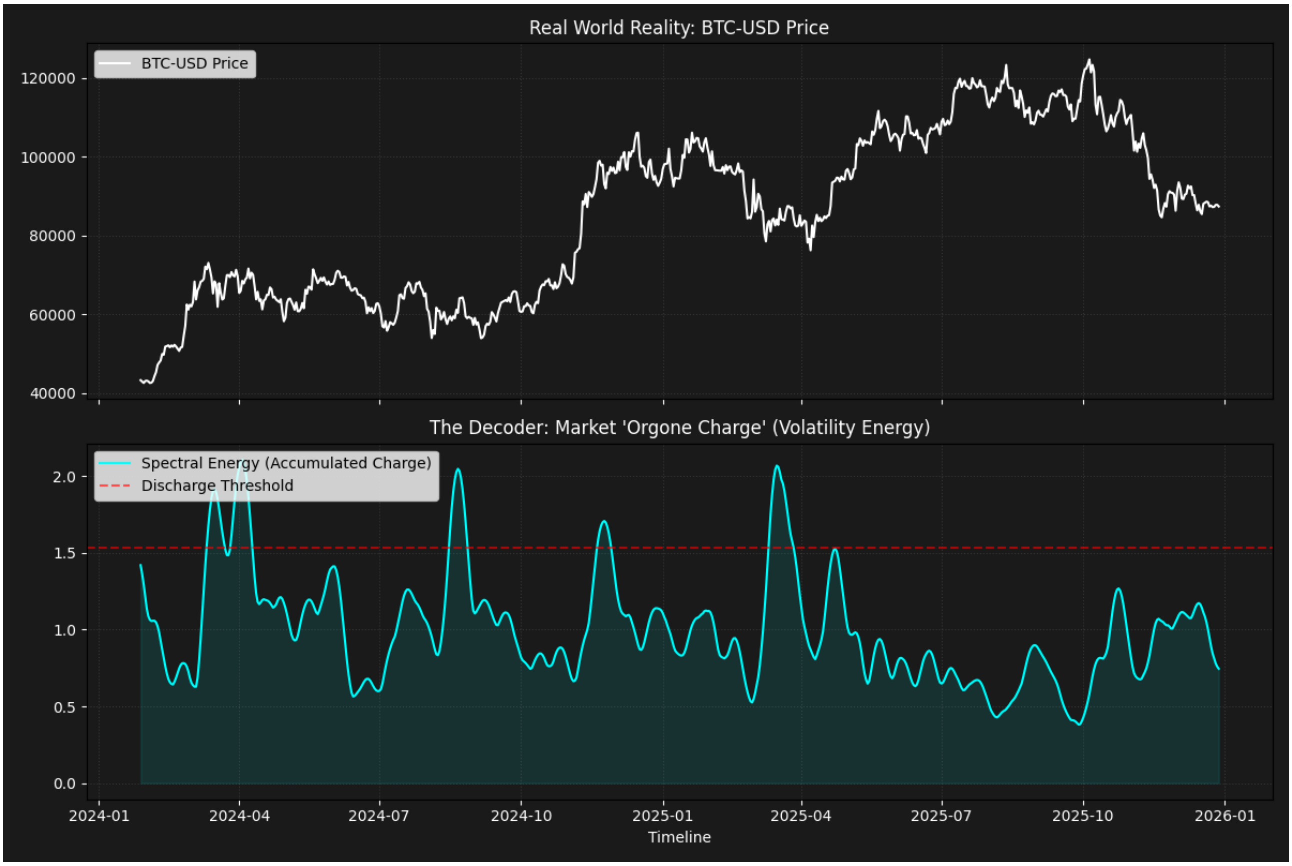


Figure 1: **Total Spectral Energy vs. Price Action (Daily View).** The bottom panel shows the aggregated "Orgone Charge" of the market. Note how spikes above the red dashed threshold (e.g., March 2024, March 2025) precede or coincide with significant trend reversals or crashes, indicating an unsustainable level of vibrational energy.

Observation of Figure 1 confirms that markets rarely crash from a state of low energy. Major downtrends are almost invariably preceded by a spike in spectral vibration above the critical threshold, validating the hypothesis of "charge accumulation" before discharge. Conversely, periods of low spectral energy correspond to stable, laminar price trends.

## 3.2 Actor Identification via Frequency Separation

The secondary analysis, utilizing hourly data, separated the high-frequency (magenta) and low-frequency (cyan) signals to identify the intent of market participants. The results are presented in Figure 2.

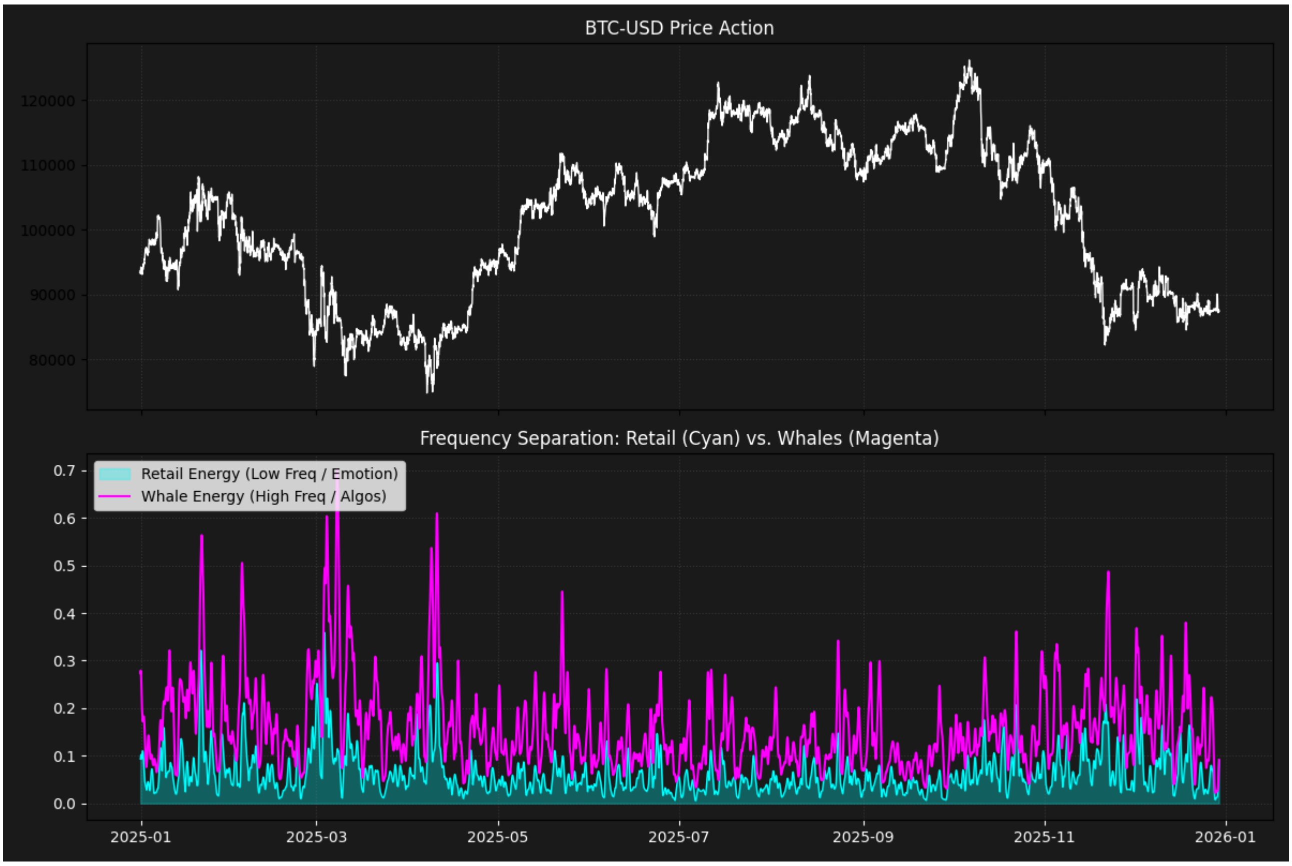


Figure 2: **High-Frequency (Whale) vs. Low-Frequency (Retail) Energy (Hourly View).** This chart separates market participants by their operational speed. Divergences between the magenta line (Algos) and cyan area (Retail) offer insight into "smart money" positioning versus herd sentiment.

Figure 2 reveals distinct behavioral patterns:

1. **High Conflict Zones (Feb-Mar 2025):** Periods where both high and low-frequency energies spike simultaneously indicate maximum volatility and unified panic/euphoria across all market participants.

2. **Smart Accumulation (May 2025):** A significant divergence occurs where high-frequency algorithmic energy remains active (magenta spikes) while low-frequency retail energy becomes dormant (flat cyan area). This indicates institutional accumulation occurring quietly while retail interest is low. This pattern immediately preceded a major price breakout from \$80k to over \$120k.

# 4 Conclusion

This experiment demonstrates that treating financial markets as functional energetic systems, rather than purely statistical ones, yields actionable predictive insights. By applying spectral analysis principles derived from wave theory, we successfully identified latent volatility potential before it manifested in price. Furthermore, by segmenting frequencies, we established a viable methodology for distinguishing the quiet accumulation of algorithmic actors from the noisy sentiment of retail traders.