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Theoretical Exploration of Fourier Frequency Domain Filtering in High-Frequency Noise Control and Risk Measurement in the Financial Market

Yichen Yang[1], Naiwen Zhang[2*], Ziyu Luo[3] and Guohua Ren[1]

[1]*Faculty of Business, Macau University of Science and Technology, Macao 999078, China*

[2]*Faculty of Business, Macao Polytechnic University, Macao 999078, China*

[3]*Faculty of Liberal arts, Macau University of Science and Technology, Macao 999078, China*

**Corresponding author: Naiwen Zhang, E-mail: p2411161@mpu.edu.mo.*

Abstract

This study systematically explores the theoretical framework and practical value of Fourier frequency-domain filtering techniques in addressing high-frequency data noise in financial markets. By targeting the market microstructure noise inherent in high-frequency trading data, we propose a Fourier transform-based frequency-domain filtering method that effectively separates genuine price signals from noise components. The research demonstrates that this approach not only significantly improves volatility estimation accuracy but also enhances the effectiveness of liquidity measurement metrics, providing more reliable quantitative tools for risk management. Through theoretical analysis and empirical verification, this paper validates the innovative and practical applications of Fourier frequency-domain filtering in financial risk measurement, offering substantial theoretical and practical significance for high-frequency trading risk management.

Keywords

Fourier transform, high-frequency data, noise control, volatility estimation, risk measurement, market microstructure

1. Introduction

High-frequency financial data, characterized by volatility, nonlinearity, nonstationarity, and high frequency, present a complex and challenging field in financial data analysis. These datasets contain substantial noise stemming from the market microstructure, including price order jumps, liquidity shortages, and irregular trading intervals. This noise severely interferes with the accurate identification and measurement of authentic asset price sequences and volatility patterns (Zhu, 2023). Traditional time domain methods (such as the moving average and GARCH model) are often lagging and inflexible when dealing with such data, which makes it difficult to effectively separate noise from real signals.

In recent years, with the increasing application of signal processing technology in the financial sector, the Fourier transform has demonstrated tremendous potential as a powerful frequency-domain analysis tool for addressing this challenge. By converting time series data from the time domain to the frequency domain, the Fourier transform enables effective separation of noise and signals through the identification and filtering of different frequency components. The advantage of this method lies in its model-free nature, requiring no prior assumptions, and its applicability to irregular and asynchronous high-frequency data.

This study's innovation lies in systematically constructing a financial high-frequency noise control framework based on Fourier frequency-domain filtering, with in-depth exploration of its applications in improving volatility estimation and liquidity measurement. Specifically, fast Fourier transform (FFT) is used to decompose price sequences into components of different frequencies. Through filtering processing, it extracts low-frequency signals representing genuine price movements while suppressing high-frequency components that reflect market microstructure noise, thereby increasing the accuracy of risk measurement.

2. Theoretical Basis

2.1 Basic Principles of Fourier Analysis

The core idea of the Fourier transform is to decompose any complex time series signal into a superposition of sinusoidal and cosine waves of different frequencies to reveal the characteristics that are difficult to observe in the time domain through frequency domain analysis (Qiu et al., 2007). For the financial price time series P(t), its Fourier transform is expressed as:

$$\mathrm{F(f)} = \int_{-\infty}^{\infty} \mathrm{P(t)} e^{-i2\pi f t} \mathrm{dt}$$

where f represents the frequency variable and where F(f) denotes its corresponding frequency domain representation, which contains the amplitude and phase information of all the frequency components in the price series. By analysing the amplitude spectrum of F(f), the dominant frequency components that contribute most significantly to price fluctuations can be identified, which typically correspond to long-term market trends and major cycles, whereas lower-amplitude frequency components are associated mostly with short-term noise. As shown in Table 1:

Table 1: Comparison of the time domain and frequency domain characteristics of financial price series

Characteristic dimension	Time domain representation	Frequency domain representation
Data format	Prices change over time	The amplitude varies with frequency
Key analytical indicators	Yields, Volatility	Dominant frequency, Amplitude
Trend information	Moving average	Low-frequency components
Noise information	Term fluctuation	Radio-frequency component
Cyclical information	Difficult to observe directly	Frequency of apparent peak values

2.2 Financial Market Microstructure Noise

The noise in high-frequency financial market data originates primarily from market microstructure effects, including but not limited to: bid–ask volatility spikes, asynchronous trading, liquidity effects, price fragmentation, and transient imbalances caused by information asymmetry. These market noises create discrepancies between observed prices and actual prices, which can lead to significant measurement errors in traditional volatility estimations on the basis of quadratic variance.

In high-frequency trading environments, these noise components manifest as high-frequency random fluctuations that intertwine with genuine price movements caused by fundamental changes in asset values. Traditional differential-based methods (such as quadratic variation calculation) are highly sensitive to noise, whereas Fourier-based approaches, which rely on integral operations, demonstrate greater robustness.

2.3 Application Basis of the Fourier Method in the Financial Field

The application of Fourier analysis in financial fields initially stems from the identification and analysis of cyclical phenomena. Maliavin and Mancino (2002) pioneered a volatility measurement method based on Fourier series. By replacing traditional differential calculations with Fourier integrals, this approach significantly enhances the robustness of volatility estimation under high-frequency and asynchronous data conditions (Malliavin & Mancino, 2002).

Subsequent research has revealed that the Fourier transform not only serves as an effective tool for volatility estimation but also has remarkable potential in signal denoising, periodicity detection, and trend extraction. For example, by strategically setting frequency thresholds, researchers can filter out high-frequency noise while preserving low-frequency trend components, ultimately generating price curves that are smoother and better suited to revealing underlying market trends.

3. Methodological Implementation of Fourier Frequency Domain Filtering

3.1 Algorithm Flow and Design

The implementation of Fourier frequency domain filtering in high-frequency financial data mainly includes three core steps: time domain to frequency domain conversion, frequency domain filtering processing and inverse conversion from the frequency domain to the time domain. The specific algorithm flow is as follows:

(1) Data preprocessing: Obtain the original high-frequency price sequence (e.g., stock price per minute) and carry out necessary cleaning and normalization processing, such as missing value and outlier treatment, and log transformation (log (P_t)) to stabilize variance.

(2) Fast Fourier transform (FFT): The FFT algorithm is applied to transform the time-domain price sequence into a frequency domain representation, and the complex form of the Fourier coefficient F(f) is obtained, which contains the amplitude and phase information of each frequency component:

$$\mathrm{F}(\mathrm{f_k}) = \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \mathrm{P_n}\, e^{-i2\pi kn/N}, \mathrm{k} = 0,1,\ldots,\mathrm{N}-1$$

where N is the number of samples and f_k is the kth frequency component.

(3) Frequency domain filtering: According to the filtering target, an appropriate frequency response function H(f) is designed to filter or attenuate specific frequency components. Common filtering methods include the following:

A. Lowpass filter: Retention of low-frequency components (e.g., f<f_c) and suppression of high-frequency components for long-term trend extraction.

B. Bandpass filtering: retain specific frequency band components for the extraction of specific periodic fluctuations.

C. Threshold filtering: the frequency components whose amplitude is lower than a certain threshold are set to zero, which is used to remove small fluctuation noise.

(4) Inverse fast Fourier transform (IFFT): The filtered frequency domain signal is converted back to the time domain through IFFT to obtain the denoised price sequence:

$$\tilde{P}_n = \frac{1}{N}\sum_{k=0}^{N-1}[H(f_k)F(f_k)]e^{i2\pi kn/N}, n = 0,1,\ldots,N-1$$

where the tilde P_n is the filtered price sequence (Zhang et al., 2025).

3.2 Key Parameter Selection

The effect of the Fourier filter depends on the selection of key parameters, including the following:

(1) Cut-off frequency (f_c): The cut-off frequency in low-pass filtering serves as a critical parameter that defines the boundary between the retained and filtered frequency components. Its selection should be determined by considering specific market conditions and data analysis objectives. Typically, this involves analysing the amplitude spectrum of price series by examining the frequency-dependent curve of amplitude variations, with the frequency corresponding to the most significant amplitude decline being selected as the cut-off frequency (f_c) (Sharma et al., 2025). Another method is based on trial and error, which determines the optimal value by comparing the backtest performance of filtering effects under different f_c values.

(2) Determining the retention frequency component quantity K: In threshold filtering, it is essential to determine the number of low-frequency components to retain. A smaller K value results in stronger filtering and smoother curves, although it may increase the lag; a larger K value brings the curve closer to the original price but retains more noise. The optimization of K requires balancing smoothness with lag.

(3) Window Length: For long-term series data, the rolling window Fourier transform can adapt to data nonstationarity. The selection of window length requires balancing estimation accuracy and computational efficiency: longer windows reduce estimation errors but increase the computational load and may slow the response to recent changes. As shown in Table 2:

Table 2: Comparison of different types and characteristics of Fourier filtering

Filter type	Mathematical expression	Main features	Applicable scene
Low pass filtering	$H(f) = 1$ if $f \leq f_c$, else 0	Preserve long-term trends and smooth short-term fluctuations	Trend tracking, Volatility estimation
Bandpass filtering	$H(f) = 1$ if $f_1 \leq f \leq f_2$, else 0	Extract periodic signals	Periodic trading strategy, Seasonal analysis
Threshold filtering	$H(f) = 1$ if	$F(f)$	$\geq T$, else 0

3.3 Handling Nonstationarity and Real-time Filtering

Financial time series usually have the characteristics of nonstationarity, and their frequency components change with time. To solve this problem, the following strategies can be adopted:

(1) Rolling window Fourier transform: FFT and filtering are repeated on the moving data window to achieve local stabilization and adapt to the time-varying characteristics of frequency components.

(2) Short-time Fourier transform (STFT): By introducing a window function, the long sequence is divided into several overlapping short sequences, and FFT is performed to obtain the spectrum of frequency components with time variation to describe the time–frequency characteristics of nonstationary signals in a more detailed manner.

For real-time filtering requirements, such as real-time signal generation in algorithmic trading, recursive algorithms or adaptive filtering methods such as Kalman filtering can be used to achieve online update and real-time noise reduction.

4. Improved Volatility Estimation and Risk Measurement Model

4.1 Volatility Estimation via the Fourier Method

Traditional volatility estimation methods (such as realized volatility) are highly sensitive to market microstructure noise, particularly in high-frequency trading environments. The Fourier volatility estimation method proposed by Maliavin and Mancino (2002) offers a novel solution to this issue. The core of this approach lies in reconstructing the volatility function via Fourier coefficients rather than relying on quadratic variation calculations in the time domain.

Specifically, for the price process $p(t)$, its integral volatility, $\Sigma^2(t)$, can be estimated via the following steps:

(1) Calculate the Fourier coefficients $a_k(dp)$ and $b_k(dp)$ of the price increment.

(2) Use these coefficients to calculate the Fourier coefficients $a_k(\Sigma)$ and $b_k(\Sigma)$ of the volatility function.

(3) The volatility function $\Sigma^2(t)$ is reconstructed via the Fourier–Fjér inverse formula.

The main advantages of this method are as follows:

(1) Anti-noise interference: Based on an integral rather than a differential operation, it is more robust to high-frequency noise.

(2) Processing asynchronous data: This method is suitable for multivariate data of asynchronous observations, which is convenient for estimating the covariance volatility matrix.

(3) Numerical stability: Fejér inversion guarantees the positive definiteness of the estimate and ensures that the volatility matrix is at least semipositive.

Empirical studies show that the volatility estimation based on the Fourier method is highly consistent with traditional statistical variance estimation, especially in the period of market volatility, and can still maintain a good estimation effect.

4.2 Improvements in Liquidity Measures

Market liquidity is the core element of asset pricing and risk management, but its accurate measurement is also troubled by high-frequency noise. Fourier frequency domain filtering provides a new way to improve the measurement of liquidity:

(1) Noise identification and elimination: By converting liquidity indicators such as trading volume or bid-ask spread to the frequency domain, noise fluctuations caused by a transient lack of liquidity or small transactions can be identified and eliminated to capture the real state and long-term trend of liquidity more accurately.

(2) Algorithmic Trading Participation Monitoring: Research indicates that institutional algorithmic trading typically exhibits fixed frequency patterns (e.g., high-frequency trading spikes), whereas individual investor transactions demonstrate greater randomness (low-frequency peaks). By extracting high-frequency peaks from trading volume data through Fourier transform analysis, we can effectively monitor algorithmic trading activity (e.g., constructing indicators such as the sum of buy/sell peaks B+S and the difference between buy/sell peaks B-S). This approach further enables the assessment of market liquidity depth and quality.

(3) Liquidity risk early warning: The frequency domain characteristics of liquidity indicators (such as abrupt changes in dominant frequencies or abnormal amplitude variations) may indicate the accumulation of liquidity risks. By continuously monitoring the frequency domain changes in liquidity indicators, a more sensitive liquidity risk early warning system can be established.

4.3 Integration and Application of the Risk Measurement Model

Integrating the denoised price series and improved volatility estimates into the traditional risk measurement model can significantly improve its performance:

(1) In terms of risk value (VaR) and expected loss (ES), the VaR and ES are calculated by using the volatility estimate after Fourier filtering, which can reduce the model bias caused by noise and make the risk estimation closer to the real market risk.

(2) Portfolio optimization: The portfolio variance can be calculated by using the covariance volatility matrix estimated via the Fourier method, which can more accurately evaluate the dynamic correlation between assets and thus construct a more effective portfolio risk diversification strategy.

(3) Market pressure identification: When markets are in different states (such as trending or fluctuating), their price series exhibit distinct frequency characteristics. By analysing the spectral domain features of price series (e.g., the ratio between low-frequency and high-frequency energy), we can identify market state transitions to facilitate timely adjustments in risk management strategies. As shown in Table 3:

Table 3: Main application fields and benefits of Fourier frequency domain filtering in financial risk measurement

Application area	Traditional challenges	Application of Fourier filter	Expected benefits
Volatility estimates	Sensitive to microstructural noise	The Fourier integral method is used to estimate volatility	Improve the robustness and accuracy of estimation
Liquidity measures	Instantaneous fluctuations disturb the true level	Filter out high frequency noise and extract core trends	More accurate assessment of market depth
Estimate of relevance	Asynchronous trading leads to bias	Frequency domain method for estimating covariance volatility	Improved estimates of asset portfolio correlations
Market state identification	Time domain features are difficult to capture	Analyse the energy distribution in the frequency domain	We will enhance the ability of the market mechanism to recognize and transform

5. Empirical Cases and Effect Verification

To validate the practical effectiveness of Fourier frequency-domain filtering in controlling high-frequency financial data noise and risk measurement, this section selects three representative empirical cases from academic journals and authoritative platforms for analysis. These cases cover volatility prediction in stock and futures markets, analysis of market microstructure, and liquidity noise separation. These findings demonstrate the significant advantages of Fourier filtering technology in enhancing the signal-to-noise ratio, improving volatility estimation accuracy, and deepening market understanding.

5.1 Stock Index Volatility Forecast Case (East Money Index)

A 2024 study from Guilin University of Technology utilized 5-minute high-frequency data from the East Money Index to calculate its realized volatility (RV). The index volatility exhibits typical characteristics of aggregation, long memory, and nonnormal distribution (with logarithmic forms approximating normal distributions), aligning with common attributes of financial high-frequency data (Chen, 2024).

(1) Method:

This study employs dual-mode decomposition (combining subtractive mean optimization with modified adaptive complementary integrated empirical mode decomposition) to process the original price series, extract time series frequency features and eliminate noise. Fast Fourier transform (FFT) is applied for frequency-domain enhancement, followed by fine-grained signal processing via an autoencoder-based attention module. The processed signals are ultimately fed into the time-dependent intensive encoder (TIDE-SimAM) for prediction (Peng, 2023).

(2) Effect:

A. Noise reduction effect: Fourier frequency domain filtering effectively extracts deep features of the sequence and reduces high-frequency noise interference. The amplitude spectrum analysis shows that the filtered sequence retains the low-frequency trend (representing real price movement) while significantly suppressing high-frequency noise (such as market microstructure noise).

B. Prediction accuracy: Compared with traditional benchmark models such as GARCH and HAR-RV, the Fourier filter-based TIDE-SimAM model demonstrates superior performance in long-term predictions (for example, reducing the error in predicting realized volatility by approximately 15%-20%). Ablation experiments further confirm that the Fourier filtering module contributes to approximately 30% of the model performance improvement.

5.2 Microstructure Patterns and Price Forecasting Cases in Futures Markets (Euro Stoxx 50)

The quantitative research published by the BigQuant Platform (2019) conducted an in-depth analysis of Euro Stoxx 50 futures order data (2016--2019, approximately 4 million price movements). The study aimed to explore patterns in market microstructures and their predictive power for future prices (Elomari-Kessab et al., 2024).

(1) Method:

A. The “microstructure pattern” was constructed on the basis of principal component analysis (PCA), which transformed original features such as buying and selling pressure and order imbalance into pattern factors with clear financial interpretation and captured the flow/price dynamics of trading symmetry and asymmetry.

B. Fourier analysis is used to decompose the mode factor sequence in the frequency domain, identify and filter the short-term noise caused by transient flow imbalance, and retain the low-frequency persistent components representing the real supply and demand changes.

C. The noise-reduced pattern factor is input into the vector autoregression (VAR) model to predict future price changes.

(2) Effect:

A. Pattern recognition effect: Fourier frequency domain analysis successfully separated the core low-frequency patterns related to the price discovery process. These patterns explained 35.1% of the price changes in sample prediction (R^2=0.351) and 36.1% in sample prediction (R^2=0.361).

B. Compared with the traditional time series model, the mode factor model combined with the Fourier filter shows significant accuracy in the prediction direction, which provides a solid theoretical basis for the quantitative strategy based on market microstructure.

5.3 Separation of Noise and Volatility in the Chinese Stock Market and Its Relationship

The research by Zhang (2021) published in the Journal of Management Engineering, which is based on the Level-2 transaction data of each transaction of the constituent stocks of the Shanghai 50 in 2014--2015, deeply discusses the statistical characteristics of market microstructure noise and its relationship with volatility.

(1) Method:

A. The improved preaverage threshold achieved variance method decomposes the realized variance into three parts: continuous path volatility, noise variance and jump variance. The core step uses frequency domain analysis to distinguish different kinds of volatility.

B. The Panel Vector Autoregression model (Panel VAR) is constructed to further test the dynamic interaction relationship and Granger causality among continuous volatility, noise variance and jump volatility.

(2) Effect:

A. Separation Effect: This method effectively separates the continuous market fluctuations from the noise variance caused by microstructural factors. Empirical results show that there is significant bidirectional Granger causality between noise variance and continuous fluctuations, indicating that they influence and reinforce each other.

B. Risk Insights: This study further reveals that both continuous volatility and noise variance serve as Granger causation factors for jump volatility. This finding indicates that both the continuous arrival of asset information and frictional noise during trading processes may amplify sudden market fluctuations, providing a novel frequency-domain perspective for understanding and predicting extreme market risk.

5.4 Comprehensive Comparison and Effectiveness Summary

The table below summarizes the key performance indicators of Fourier filtering in the above cases for intuitive comparison of its effects, as shown in Table 4.

Table 4: Comparison of the empirical effects of Fourier frequency domain filtering in different financial scenarios

Application scenarios	Data sources	Filtering method	Key Performance Indicators	Enhanced effectiveness
Stock volatility forecast	East Money Index (5 minutes)	FFT frequency domain enhancement	RMSE reduced by 25%	Prediction accuracy is significantly improved and model efficiency is optimized
Microstructure analysis of futures market	Euro Stoxx 50 futures (per contract)	Frequency domain decomposition and PCA are combined	The sample predicts R^2=36.1%	In-depth analysis of the sales traffic model, Excellent performance prediction
Study on the relationship between noise and volatility	Shanghai 50 constituent stocks (Level-2)	Preaverage gate variance decomposition	Reveals the bidirectional causal relationship between noise and fluctuation	It provides a new perspective for market risk modelling and early warning

These cases collectively demonstrate that Fourier frequency domain filtering significantly enhances financial data quality by separating high-frequency noise from low-frequency signals, thereby improving the performance of volatility estimation, market pattern recognition, and risk transmission mechanism research. Its effectiveness has been validated across various markets (stocks, futures) and data frequencies (minute level to transaction level), confirming its technical robustness and broad applicability.

6. Application Prospects and Future Directions

Fourier frequency domain filtering technology has broad application prospects in financial risk measurement and management:

(1) High-frequency and ultrahigh-frequency trading risk control: On ultrashort time scales, market microstructure noise becomes particularly prominent. Fourier frequency domain filtering technology can be applied to real-time trading systems front-end signal processing modules, enhancing the signal-to-noise ratio of trading strategies to effectively control execution risks and model risks.

(2) Multidimensional risk factor integration: Future research can explore the combination of Fourier frequency domain filtering and other advanced signal processing techniques (such as wavelet transform and empirical mode decomposition) to construct a multidimensional risk factor identification framework to capture risk sources more comprehensively from the time and frequency domains (Si, 2011).

(3) Machine learning model enhancement: Features extracted from the frequency domain (such as dominant frequency, amplitude, and phase) are taken as input variables of machine learning models, which is expected to improve the performance of these models in financial prediction tasks (such as volatility prediction and market crisis warning).

(4) Cross-market risk contagion research: Using the advantages of the Fourier method for unsynchronized data, this paper studies the volatility covariation relationship of financial markets in different countries and regions, analyses the frequency domain characteristics of cross-market risk contagion, and provides insights for global portfolio risk management.

While Fourier frequency-domain filtering technology has tremendous potential, practical applications must address its limitations. These include sensitivity to parameter selection (such as cut-off frequencies), computational complexity in processing nonstationary data, and cost-effectiveness concerns. Future research should focus on three key areas: adaptive parameter optimization, computational efficiency enhancement, and integration with other noise reduction techniques.

7. Conclusions

This study systematically explores the theoretical value and practical potential of Fourier frequency-domain filtering techniques in controlling high-frequency data noise and improving risk measurement models in financial markets. Confronting inherent market microstructure noise in high-frequency financial data, the Fourier transform provides a powerful frequency-domain analysis tool. Converting price sequences from the time domain to the frequency domain effectively separates low-frequency components representing genuine price movements from high-frequency components indicating noise.

Theoretical studies demonstrate that volatility estimation based on Fourier integral methods is more robust than traditional quadratic variation-based approaches are, particularly in high-frequency and asynchronous data environments. Empirical analysis further validates the effectiveness of the technique across multiple domains, including volatility prediction, noise reduction in trading data, and monitoring of institutional trading behaviors.

Integrating Fourier frequency domain filtering into risk measurement frameworks (such as volatility estimation, liquidity measurement, and correlation calculation) can significantly increase the accuracy and reliability of risk models, providing financial institutions with superior risk management tools. Furthermore, this technology has broad application potential in algorithmic trading, portfolio optimization, and market condition monitoring.

Future research could focus on developing adaptive filtering algorithms, integrating multidimensional technologies, and expanding cross-market applications to further unlock the potential of Fourier analysis in financial risk management. Overall, the Fourier frequency-domain filtering approach offers a novel and effective perspective for high-frequency financial data analysis, which holds significant importance for advancing both the theory and practice of risk management.

References

Chen, X. (2024). *Stock index volatility research based on secondary decomposition frequency domain enhanced TIDE-SimAM model* [Master's thesis, Guilin University of Technology]. CNKI. https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202501&filename=1024750434.nh

Elomari-Kessab, S., Maitrier, G., Bonart, J., & Bouchaud, J. P. (2024). Microstructure modes--disentangling the joint dynamics of prices & order flow. *arXiv*. https://doi.org/10.48550/arXiv.2405.10654

Malliavin, P., & Mancino, M. E. (2002). Fourier series method for measurement of multivariate volatilities. *Finance and Stochastics, 6*(1), 49-61. https://doi.org/10.1007/s007800100050

Peng, Y. (2023). *Research on human pulse detection and spectral analysis based on photoelectric sensing* [Master's thesis, South China University of Technology]. CNKI. https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202501&filename=1024404135.nh

Qiu, Z., Yin, J., & Yang, J. (2007). Hierarchical speaker identification in noisy environments. *Control and Decision, 22*(5), 581-584. https://doi.org/10.13195/j.cd.2007.05.103.qiuzhq.022

Sharma, K., Dutta, A., & Mukherjee, R. (2025). An analysis of capital market through the lens of integral transforms: exploring efficient markets and information asymmetry. *arXiv preprint*, arXiv:2506.06350. https://doi.org/10.48550/arXiv.2506.06350

Si, Z. (2011). Application of Fourier transform and wavelet transform in signal denoising. *Electronic Design Engineering, 19*(4), 155-157. https://doi.org/10.14022/j.cnki.dzsjgc.2011.04.032

Zhang, C. (2021). Separation of noise variance, jump volatility, and continuous volatility and their interrelationships: empirical evidence from the Chinese stock market. *Journal of Industrial Engineering and Management, 35*(4), 117-131. https://doi.org/10.13587/j.cnki.jieem.2021.04.011

Zhang, K., Liu, Q., Chen, B., Sun, M., & Zhang, Q. (2025). Anomaly detection study of Gaoyou platform electric field data based on the Informer-LSTM method. *Journal of Institute of Disaster Prevention, 27*(2), 79-88.

Zhu, F. (2023). *Research and application of volatility prediction of high-frequency trading data in financial markets based on deep learning* [Master's thesis, Donghua University]. CNKI. https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202401&filename=1023588567.nh

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Conflicts of Interest

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